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Mediation analysis of public emotions in response to policy implementation performance during crises: the case of COVID-19 management policies in the UK

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ABSTRACT
Understanding public emotions in crises is crucial to effective public policy management for governments. This study examines the relationship between pandemic management policies, pandemic management performance, and fundamental emotions according to Plutchik's Wheel of Emotion, in the context of COVID-19 in the UK. Our findings validate the role of emotions in shaping political events and then suggest the involvement of emotions, namely fear and surprise, as mediators in government policies and their subsequent outcomes in pandemic management. The study contributes to the public policy management literature by emphasizing the importance of the heterogeneity of emotions.

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KEYWORDS COVID-19; government policy; public emotions; pandemic management performance; mediation analysis

Introduction

Effective governmental policy orchestration is widely acknowledged as pivotal in enhancing management capacity during crises, as exemplified by the COVID-19 pandemic (Zheng, Hongxia, and Sun 2021). Since 2020, governments globally have implemented unprecedented policies to mitigate the impact of COVID-19 and ensure the continuity of healthcare services (Lipscy 2020). Investigating policies for public health crisis management facilitates a critical examination of the fundamental components of public management: the presumed links between ideology, actions, and outcomes (Osborne 2002), Therefore, this research initiative aims to enhance government accountability, transparency, and collaboration among stakeholders, including healthcare providers, policymakers, and the general public (Minyoung, Su Kim, and Seong Soo 2022).

Due to policy interventions that drastically restricted people's daily lives (Haug et al. 2020), public emotions, following the initially predominant social environmental

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messages addressing crisis-related human responses, became the next most prevalent information circulating on social media (Reuter and Kaufhold 2018). In light of the understanding that the general public is not solely a passive recipient of authoritative messages and acknowledging that emotional cues can offer valuable insights not previously considered in pandemic management policies, diverse public emotions are unequivocally recognized as pivotal factors influencing the outcomes of pandemic management (Chou and Budenz 2020; Heffner, Vives, and FeldmanHall 2021; Jungmann and Witthöft 2020). However, the extant literature on public health management and pandemic management has insufficiently addressed the pivotal role of public emotions, resulting in a scarcity of research on their potential impacts on pandemic management performance (Auger et al. 2020; Lyu, Le Han, and Luli 2021; Turner 2022). In particular, the need for a more granular investigation into how various emotional components contribute differentially to this process has been overlooked. Additionally, the complex relationships among management policies, public emotions, and pandemic management performance have not been systematically explored, with a notable absence of fine-grained analyses addressing the diversity of policy types. Hence, research into the underlying mechanisms of pandemic management should integrate a comprehensive examination of various government policies and the heterogeneous role that public emotions play in policy implementation.

Rooted in the Affective Intelligence Theory (AIT), our study endeavours to illuminate the manner in which individuals' emotions are shaped by public policies, subsequently impacting the management performance of specific societal occurrences (Marcus, Russell Neuman, and MacKuen 2000). The AIT, as a sociological framework, is dedicated to comprehending how emotions exert influence on human decision-making within the realm of political events. Nonetheless, a noteworthy observation is that a significant portion of contemporary research utilizing this theory tends to either focus on general emotional polarity or partial emotional expressions, thereby overlooking the opportunity for a more in-depth and comprehensive exploration of emotional components, especially within the context of crisis scenarios (Erhardt et al. 2021; Wamsler et al. 2023). Therefore, our theoretical innovation lies in our commitment to a more nuanced examination of the AIT, empowering us to intricately dissect the relationships between government policies, public emotions, and pandemic management, thereby enriching the interpretation of the theory.

To address this matter, we collected data from Twitter in the UK, spanning from February 2020 to January 2022, and employed text mining techniques and regression analysis methods to examine the relationship between government policies, public emotions, and pandemic management performance within the context of the COVID-19 crisis. Specifically, four policies (i.e. containment, economic, health, and vaccination) are included to explore the intervening mechanisms of public emotions including anger, disgust, fear, joy, sadness, surprise, trust, and anticipation, as delineated by Plutchik (1980)'s wheel of emotions. Additionally, pandemic management performance is described using the reproduction number, a crucial epidemiological parameter assessing the virus transmissibility (Liu et al. 2021). Overall, our findings validate the significant influence of emotions in shaping political events and subsequently unveil the role of specific emotions, namely fear and surprise, as mediating factors in government health and economic policies and their impacts on pandemic management. However, other emotions do not exert similar effects.

In summary, this research contributes significantly to the literature in the field of public management and policy administration. Theoretically, our results supports and enriches AIT by demonstrating that public emotions, stemming from diverse government policies, influence policy effectiveness through mediating mechanisms (Marcus, Russell Neuman, and MacKuen 2000). Moreover, we confirm earlier research that diverse policy settings impact emotions of the same polarity distinctively (Liu, Shahab, and Hoque 2022). Further, our study contributes to optimizing policy evaluation in public policy management models by articulating scenarios where public emotions potentially impact pandemic management performance (Jones and Howard Chase 1979). Regarding policy contributions, we suggest to closely monitor fluctuations in public emotions to enhance public health rapid response capacity of public health system (Zheng, Hongxia, and Sun 2021). Additionally, the implementation of a sentiment engine that links fluctuations in public emotions with the reproduction number is suggested. Given the quantitative relationship we have identified between public emotions and the reproduction number, the engine can notify policymakers of critical situations in which a specific emotion exceeds a threshold, potentially resulting in uncontrolled virus transmission, as indicated by the reproduction number. This enables policymakers to prioritize addressing the needs of populations experiencing elevated emotional stress to mitigate widespread virus transmission.

Literature and hypotheses

Theoretical background

Emotions have gained prominence within the realm of public management across various domains, serving as crucial factors in explaining the differential success levels of government decisions of managing specific public events (Cox and Béland 2013). These domains encompass areas such as political issue management (Vasilopoulos 2019), public health (Renström and Bäck 2021), public communication (Lee and Choi 2018), and social movements (Jasper 2011). The prevailing theory commonly connected for this cross-disciplinary research is the AIT, which explains how individual responses are directed by public policies through two emotional systems (Marcus, Russell Neuman, and MacKuen 2000). We employed AIT as the theoretical lens for this study, considering its suitability based on three reasons as follows.

First, AIT, drawing upon its core definition, offers useful guidance in understanding how individual responses are directed by government policies through emotions, consequently impacting the performance of managing a crisis like COVID-19. Along with endeavours in medical treatment development (Korber et al. 2020), it should be noted that despite the government's implementation of various policies aimed at regulating individual behaviours to mitigate virus spread (Min et al. 2020), there continues to be a concern about policy ineffectiveness in pandemic management. To explore the underlying mechanism and attain enhanced management performance, AIT holds that emotions also can shape and influence individuals' responses within a context that pertains to government policies during crises or periods of tension (Finucane et al. 2000; Marcus, Russell Neuman, and MacKuen 2000). Public emotions triggered by government management policies can have varied implications for their effectiveness, either positively or negatively. Recognizing the inherent feature of AIT, policymakers can frame policy issues more productively by identifying and responding to the emotive signals of a target audience, leading to greater policy support and ensuring the smooth operation of the entire system (Mansoor 2021).

Second, the attribution of AIT's two emotional systems – the disposition system and the surveillance system – is a pivotal mechanism in how citizens feel when confronted with government managerial policies in handling COVID-19. Disposition-system-based emotions arise when individuals encounter familiar situations where their habitual reactions no longer yield the desired outcomes (Marcus, Russell Neuman, and MacKuen 2000). Consequently, a misalignment would occur, giving rise to diverse emotional expressions across the population. This phenomenon is particularly evident when individuals are confronted with measures such as mask-wearing orders, screening tests, or contact tracing while continuing to adhere to their pre-COVID-19 routines (Kim 2021; Sanders et al. 2021). On the other hand, the activation of surveillance-system-based emotions occurs in novel or threatening circumstances, serving to sensitize individuals to perceived risks and mobilize them to make decisions based on their current emotional states during the policy implementation (Marcus, Russell Neuman, and MacKuen 2000). For example, the government policies enforcing COVID-19 vaccine introduced potential risks, including unknown side effects, leading to fear and distrust towards immunization, ultimately reducing policy efficacy and viral control efforts in the US (Hu et al. 2021).

Third, AIT enables us to integrate emotions and information in analysing the outcome of policy implementation, as the key insights of the AIT emphasized the dynamics of information processing and the significance of emotions in this regard (Marcus, MacKuen, and Russell Neuman 2011; Marcus, Russell Neuman, and MacKuen 2000). The integration allows us to uncover nuances of public emotions' role in the process of governmental administrative operation in public health crises. Facing varying degrees of perceived risks embedded in the information, it is observed that emotions, even within the same sentiment polarity (i.e. positive or negative), can serve as predictive indicators of divergent associated responses towards the event (Gaspar et al. 2016; Lee and Choi 2018; Xie et al. 2011). Considering that crises expose citizens to varying levels of risky information regarding the government's crisis response policies, insufficient crisis management may impede overall performance (Erhardt et al. 2021). Thus, the insights provided by AIT help us move beyond the binary understanding of public emotions, contributing to the development of pragmatic crisis management.

Hypotheses

Government COVID-19 policies and public emotions

The first lockdown was introduced on 23 January 2020 by the Chinese government (Ren 2020). Various official directives were then presented to mitigate the pandemic damage (Hale et al. 2021). These proliferating government policies can be categorized into four types: containment, economic, health and vaccination. Specifically, containment policies address mobility constraints in public areas, economic policies offer financial assistance, health policies primarily standardize health management practices, and vaccination policies manage vaccine availability, priority, and funding. These governmental policies have clearly pervaded all aspects of life and brought about various changes. Accordingly, the public swiftly developed diverse and dynamic emotions, such as wrath, fear, grief, joy, and trust (Liu, Shahab, and Hoque 2022; Naga et al. 2021).

Following the theoretical premise of AIT, it is clear that emotions are influenced by different government pandemic policies in two ways. Containment policies cause radical upheaval in people's habits and thus stimulate a huge discordance between the new reality and normal routine. For instance, international travel bans and school or workplace restrictions force people to adjust to an atypical pattern of human mobility, causing fear, anger and sadness (Yen et al. 2021). On the other hand, people are likely to perceive unknown risks in environments defined by economic, health, and vaccination policies, which elicits a range of emotions (Hu et al. 2021; Huang 2020). Imposed health measures, such as mask-wearing, add unexpected burdens to people's daily lives, resulting in negative sentiments (Chen et al. 2022; Sanders et al. 2021) and amplifying potential uncertainties in order to achieve its goal of minimizing infection. In contrast, certain inappropriate public health education campaigns intensify the panic of those who are already concerned and actively attempting to avoid contracting the virus (Yiping, Xiao, and Yang 2022). Feng et al. (2021) argues that economic risks also cause feelings of panic, but the overall trend of sentiments showed positive development during the study period. Moreover, vaccines are always launched with public hesitancy, and the COVID-19 vaccine is no exception. A mixed emotion of sadness and anger is present because of the potential risks of any newly-invented medical product (Hu et al. 2021). Positive emotions, such as trust and anticipation, inversely, have been shown to raise confidence in vaccines (Lyu, Le Han, and Luli 2021).

The above discussion suggests that different governments' COVID-19 policies may have varying effects on emotions. Therefore, we hypothesize that:

H1. *Governments' pandemic management policies have significant effects on public emotions.*

Specifically:

H1a. *Containment policy has significant impacts on public emotions;*

H1b. *Economic policy has significant impacts on public emotions;*

H1c. *Health policy has significant impacts on public emotions;*

H1d. *Vaccination policy has significant impacts on public emotions.*

Public emotions and governments' pandemic management performance

Plutchik (1980)'s wheel of emotions has been widely used by researchers to investigate public emotions (anger, disgust, fear, joy, sadness, surprise, trust, and anticipation). The reproduction number is vital for assessing epidemic transmissibility, projecting epidemic development trends, and designing control measures for governments' administrative work; therefore, it serves as a critical epidemiological characteristic of COVID-19 policies (Michael Lingzhi et al. 2023; Zhou et al. 2020). Existing research has investigated drivers of COVID-19 at the viral level (Korber et al. 2020) and human level, which can be further classified into protective behaviours (Min et al. 2020) and emotional responses (Chang, Chih-Hao, and Le Nguyen 2022; Feng et al. 2021). Building upon these established findings, we posit that emotions, as an additional epidemiological determinant at the human level, exert an influence on pandemic management performance.

The pandemic has caused a slew of emotions, influencing individuals thinking and conduct, since the effect of emotion on behaviours is direct (Qiu et al. 2020), and emotions affect people's attitudes and responses towards an event (Han and Baird 2022; Shaobin, Eisenman, and Han 2021). According to Gross (2014)'s seminal Emotion Regulation theory, people employ various strategies, including reappraisal, to govern their emotional responses by altering their interpretative framework. Essentially, emotions serve as informative cues guiding behavioural responses within specific contextual circumstances. Specifically, certain emotions – notably positive ones – guide individuals towards perceiving situations favourably, fostering behaviour aligned with government policies emphasizing compliance. Conversely, negative emotions may promote non-compliance with public health policies, resulting in suboptimal policy performance (D'Arcy and Teh 2019; Ormond, Warkentin, and Crossler 2019). For example, some COVID-19 vaccines have been increasingly surrounded by positive sentiments, which brings benefits in lowering viral transmissibility and more productively regulating health crises (Marcec and Likic 2022). Meanwhile, by shaping the level of compliance with governments' preventive measures, negative emotions such as fear, anxiety, and stress have a strong influence on how quickly the virus spreads (Ormond, Warkentin, and Crossler 2019; Turner 2022). People are reluctant to follow the rules, resulting in poor policy implementation, if they are anxious and fearful about newly declared regulations in the context of an unknown dangerous event (Townsend 2006).

Although these empirical studies have demonstrated that people's emotions affect their reactions towards an event, a more explicit examination of how emotions can contribute differently to government pandemic management performance has been overlooked. Therefore, we propose that:

H2. *Public emotions have significant effects on pandemic management performance.*

The mediating role of public emotions

Policies implemented by governments can prompt superior performance in managing the pandemic (Zheng, Hongxia, and Sun 2021). Recent findings have unveiled a strong association between social distancing orders and pandemic management performance, supported by empirical evidence indicating that the adoption of such policies lowers case numbers by approximately 500 per minute (Price and van Holm 2021). Health policies, including the practice of wearing facemasks, are instrumental in preventing infection via droplets (Kim 2021). Moreover, financial support policies have been proven to incentivize individuals to access to required hygiene equipment and adopt protective behaviours, thus mitigating the virus transmission (Xiaojing and Liu 2020). Furthermore, it is noteworthy that the UK government has stressed the importance of vaccination in pandemic management (Shand et al. 2022). Vaccination is a multifaceted endeavour, encompassing not only the development of safe and effective vaccines from a medical standpoint, as well as the robust implementation of vaccination policies from a public management perspective. Consequently, vaccination policy emerges as a crucial pillar in pandemic management, serving to contain outbreaks, reduce the severity of illness, and prevent the exponential growth of cases. Therefore, these observations underscore the efficiency of public health policies in contributing to pandemic management performance.

However, the pandemic policy by itself does not necessarily create an advantage for its subsequent management performance; rather, one of its by-products, namely emotions, is valuable for pandemic management performance (Turner 2022). Specifically, the explanatory power of governments' pandemic policies and their link to management performance could be influenced by the fact that these interventions elicit emotional reactions (Han et al. 2022; Renström and Bäck 2021), which further escalate or mitigate the impact of the pandemic (Lima et al. 2020). This approach reveals causal chain, starting from government policies, leading to public emotions and, ultimately, to pandemic management performance. The emerging research supports this bridging role by illustrating the dynamic character of emotions under different policies. As Renström and Bäck (2021) observed, anger supports the containment policy to limit the spread of the virus, and anxiety offers support for the economic policy. However, even for the exact same emotion, the underlying mechanism might be different. Fear encourages adaptive health-compliant behaviour, such as getting vaccinated, to promote the vaccination policy (Bendau et al. 2021), while it also contributes to decreased vaccine acceptability due to unknown side effects (Freeman et al. 2021). This discrepancy highlights the necessity of further investigation into public emotions in response to COVID-19 policies, since the intermediary mechanism of emotions could vary under different policies and thus influence governments' pandemic management performance variously.

Overall, it is evident that government policies can possess a direct influence on their practical performance, independent of emotional influences (Kim 2021; Zheng, Hongxia, and Sun 2021). However, when considering emotions' nonnegligible impacts in this process, it is suggested that emotions do not directly affect in the relationship; but instead may serve as a mediating mechanism influenced by policies, resulting in the variability in management performance (Renström and Bäck 2021). In this regard, understanding the impact that emotions have on policies can assist policymakers in developing more accurate and robust strategies for future policy development and management. Given that different government policies contribute to public emotions (H1s), which in turn impact governments' pandemic management performance (H2), we expect that heterogeneous indirect effects of emotions exist between governments'

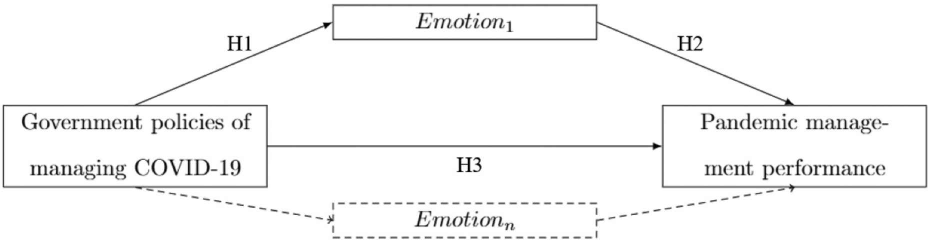

Figure 1. Main theoretical framework.

pandemic policies and their subsequent performance. Figure 1 presents the theoretical framework, and we thus propose that:

H3. *Public emotions mediate the relationship between government pandemic policies and pandemic management performance.*

Specifically:

H3a. *Public emotions mediate the relationship between containment policy and pandemic management performance;*

H3b. *Public emotions mediate the relationship between economic policy and pandemic management performance;*

H3c. *Public emotions mediate the relationship between health policy and pandemic management performance;*

H3d. *Public emotions mediate the relationship between vaccination policy and pandemic management performance.*

Methodology

Data collection and preprocessing

We have three data sources. First, daily COVID-19 cases released by the UK government from February 2020 to January 2022 are used to calculate the reproduction number. Figure 2 shows distinct peaks during the Beta, Delta, and Omicron variant periods.

Second, government policies adopted by the UK government are sourced from the Oxford COVID-19 Government Response Tracker (OxCGRT) project (Hale et al. 2021). This project, developed by Blavatnik School of Government, University of Oxford, aims to systematically gather information on various government policy responses. It records policies on a scale to reflect the extent of government action and aggregates them into

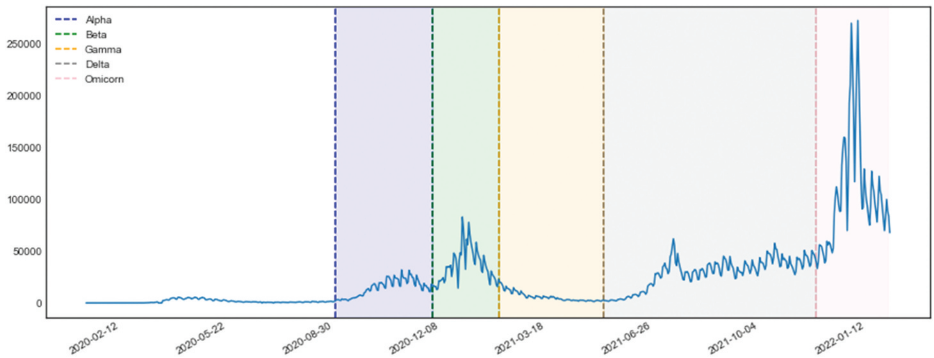

Figure 2. Cases in the UK.

a suite of policy indices. Over 400 volunteers from the University of Oxford and partner organizations collected and reviewed their data in real-time, ensuring its reliability. Ultimately, four categories of policies at the national level were included, measured using policy stringency, which denotes the degree of mandatory compliance associated with the implementation of each policy. Specifically, Table 1 presents that the containment policy is represented by eight components describing human mobility restrictions; the economic policy is represented by four components covering economic stimulus packages; eight components related to public health interventions represent the health policy; and the vaccination policy is represented using three components related to vaccine allocation. We exclude some components (highlighted in Table 1 by $), as they do not express policy stringency scales.

Third, public emotions towards the COVID-19 policies of the UK government are extracted from Twitter, with its users considered as a proxy for the general public. Utilizing the Twitter API and the Python snscrape package (TwitterSnscrape 2008), we extracted 1.2 million related tweets based on OxCGRT keywords listed in Table 2. The collected tweets are ensured to be relevant as the keywords specifically correspond to the COVID-19 management policies. By doing so, information including date, geolocation, and content was retrieved. To exclusively capture UK tweets, geolocation information was restored by extracting valid country names and mapping city names to their respective countries using the Python pycountry package (pycountry 2008) and world city data (datahub 2018). Furthermore, in cases where cities could be matched with multiple countries, we assigned the country with the largest population centre, assuming that individuals from the largest city are more likely to leave out country identifiers, as illustrated in (Chum et al. 2021). Lastly, manual extraction was employed to match user-defined city information with a standardized gazetteer at the national level using GeoNames (GeoNames 2005). This

Table 1. Government policy components.

Policy types	Components
Containment policy	school closing, workplace closing, cancelling public events, restrictions on gatherings, stopping public transport, stay-at-home requirements, restrictions on internal movement, international travel controls
Economic policy	income support, debt/contract relief ($), fiscal measures ($), international support
Health policy	public information campaigns, testing policy, contact tracing, emergency investment in healthcare ($), investment in vaccines ($), facial coverings, vaccination policy, protection of elderly people
Vaccination policy	vaccine prioritization, vaccine eligibility/availability, vaccine financial support

Table 2. OxCGRT keywords and the reliability check for policies.

Policy types	OxCGRT keywords	Reliability coefficient of its components
Containment policy	school closure, WorkFromHome, cancel event, gathering ban, transport ban, stayathome, internal travel ban, international travel ban	0.9
Economic policy	income support, debt relief, economic stimulus, international support	0.6
Health policy	health campaign, PCR, contact tracing, health investment, vaccine investment, facemask, vaccine priority, protect elderly	0.6
Vaccination policy	vaccine priority, vaccine available, vaccine investment	0.8

improved the availability rate of geolocation data from 18.7% to 61% and enabled a dataset of 141K tweets captured between February 2020 to January 2022. Also, we filtered for English-only tweets, removed HTML tags, @usernames, numbers, punctuation marks, special characters, stop words, and tokenized the text.

Measures

Independent variables

Four independent variables (containment, economic, health and vaccination policies) were calculated on a daily basis according to the formula from OxCGRT (Hale et al. 2021) as

$$I_{j,t} = 100\frac{v_{j,t} - 0.5\left(F_j - f_{j,t}\right)}{N_j}, \quad (1)$$

where $I_{j,t}$ is the policy stringency for any given sub-indicator j on any given day t; $v_{j,t}$ is the sub-indicator; $F_j$indicates that whether the sub-indicator has a flag variable ($F_j = 1$ if has, otherwise, $F_j = 0$); $f_{j,t}$ is the flag variable corresponding to different scopes of different policy types (e.g. the geographic scope of containment and health policies, the sectoral scope of the economic policy); and N_j is the maximum sub-indicator. Furthermore, we checked the consistency of all components from four policies by using Cronbach's alpha test. With scores ranging from 0.6 to 0.9 (Table 2), reliability is confirmed, meeting the suggested threshold of 0.6 (Hair 2009). Considered together, government policies range from 0 to 100, with higher values indicating stricter policies. Figure 3 displays the fluctuations of policies in the UK. It should be noted that the vaccination policy did not take effect until January 2021. The economic policy has remained highly stringent while containment and health policy fluctuated continuously across the period of study.

Dependent variable

The pandemic management performance is measured by the reproduction number, which demonstrates the average number of secondary cases of the disease caused by a single infected individual over their infectious period. We employed the Python epyestim package to estimate the reproduction number as

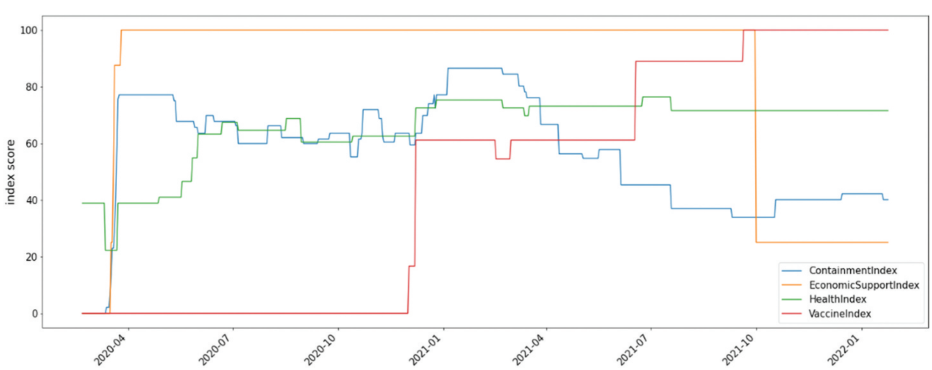

Figure 3. Government policy indices in the UK.

$$R_t = \frac{E[I_t]}{\sum_{s=1}^{t} I_{t-s} w_s} \qquad (2)$$

where R_t is the reproduction number at calendar time t; $E[I_t]$ is the expected value for new infections at t; I_{t-s} is the incidence at time step t-s; and w_s is a function to measure the risk of disease transmission, dependent on the time since an infection of the case s (Cori et al. 2013). The estimated reproduction number for each day is presented in Figure 4, revealing that the pandemic was effectively controlled after containment, economic, and health policies were launched. Notably, the reproduction number was further lowered after the vaccination policy was initiated.

Mediating variables

Plutchik (1980)'s theory, serving as a foundational framework for conceptualizing emotions in textual data, has emerged as the most useful classification scheme for emotive language analysis (Chung and Zeng 2016). Therefore, eight basic emotions – anger, disgust, fear, joy, sadness, surprise, trust, and anticipation – are used as mediating variables. To capture emotions quantitatively, a pre-trained machine learning model with an F1-score of 70.0% is applied to make predictions (Colnerič and Demšar 2018). Essentially, this pre-trained emotion recognition model employed machine learning techniques to convert textual data into numerical representations for detecting emotions. Specifically, the model was trained on a dataset of approximately 17 TB in size, comprising 73 billion tweets spanning seven years. With such settings, the model offered a universal emotion detection algorithm, not restricting only to one domain or temporal variations (Colnerič and Demšar 2018). The model was also specially trained to classify Plutchik's eight emotions using two modes: multiclass and multilabel. Multiclass was built upon a single non-binary classifier for predicting the first emotional category, disregarding any other emotional keywords present later in the tweet, while multilabel mode was operated with multiple binary classifiers, meaning one per emotional category. Based on the model performance, we chose the multiclass mode due to its highest F1-score of 70.0%.

Thus, the model exhibited accurate comprehension of the emotional meaning conveyed in tweets, resulting in the generation of eight daily emotion propensity for each tweet ranging from 0 to 1, with a higher value denoting higher intensity for each

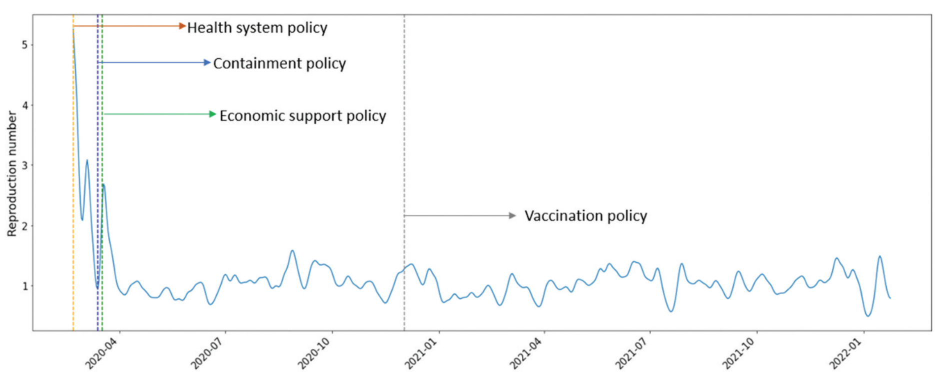

Figure 4. Reproduction number in the UK.

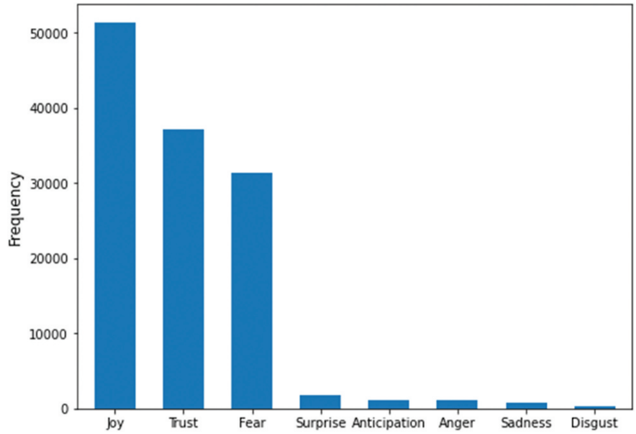

Figure 5. Distribution of emotions in the UK.

emotion category. Figure 5 presents that *Joy, Trust* and *Fear* dominate the general public's emotional range, while *Surprise, Anticipation, Anger, Sadness* and *Disgust* were rarely felt in response to COVID-19 policies during the sampling period.

Control variables

Variant stages, average policy strictness, and human mobility in open areas are included as control variables, because they are influential factors in infectious disease transmission. Specifically, variant stages are coded as 1 = no variant, 2 = Alpha, 3 = Beta, 4 = Gamma, 5 = Delta, 6 = Omicron (WHO 2022). The average policy strictness is calculated by averaging all policy stringency scores. Mobility trends for grocery and pharmacy, public transport hubs, and residential areas are captured using Google's COVID-19 Community Mobility Reports (Google 2022).

Analytic approach

Consistent with Adomako et al. (2021)'s work, the Preacher and Hayes Bootstrapping method was implemented to estimate the mediation effects of public emotions on the relationship between different government policies and pandemic management performance (Hayes 2009). This method is appropriate since it overcomes the limitation of the normal distribution assumption of indirect effect (Baron and Kenny 1986; Hayes 2009). As presented in Figure 6, X, Y and M represent the independent variable, the dependent variable and the mediator respectively. The total effect equals to the direct effect of X on Y plus the sum of indirect effects of multiple mediating variables from M_1 to M_n, which can be illustrated as

$$c = c' + \sum_{n=1}^{\infty} a_n b_n, \tag{3}$$

where c is X's total effect on Y; c' is the direct effect of X on Y; n indicates the number of mediators; a_n is the coefficient of X for the mediator M_n; b_n is the coefficient of the mediator M_n; and $a_n b_n$ is the indirect effect of M_n. Adopting this approach, we tested

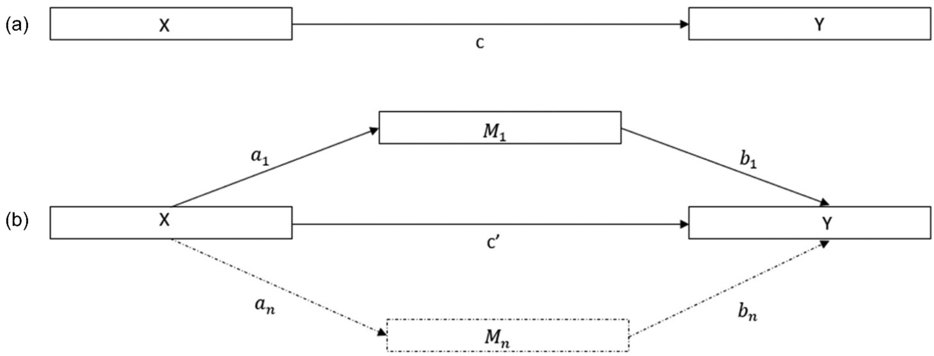

Figure 6. Mediation analysis model.

the direct effects of government policies, the indirect effects of emotions on pandemic management performance and determined if the effect was statistically significant based on the confidence interval.

Findings

The descriptive statistics and Pearson correlations are reported in Table 3. In Hypothesis 1, we analyse the effects of four government policies on different emotions and observe varying outcomes. Model 1.1 in Table 4 (containment policy) shows a significant effect on the emotion *Sadness*, suggesting that increasing containment policy stringency reduces sadness. Thus, H1a is supported. Secondly, H1b is supported, because Model 2.1 in Table 5 (economic policy) shows significant effects on emotions: *Anger, Joy, Surprise* and *Trust*. Specifically, stricter economic policy increases surprise and trust while reducing anger and joy. Thirdly, Model 1.3 in Table 6 (health policy) indicates that the policy positively predicts *Joy* while negatively impacting *Fear* and *Sadness*. The stricter the health policy is, the more joyful, less fearful, and less sad people will become, validating H1c. Finally, the vaccination policy is positively related to *Anger* and negatively related to *Trust*, supporting H1d. The results of Model 4.1 in Table 7 (vaccination policy) reflect that increasing policy stringency causes people to be angrier and less trustful.

Mediation analyses

To test mediating effects, we followed Zhao et al. (2010)'s approach. First, the independent variable and the mediator should be significantly related. Given the support for H1a, H1b, H1c, and H1d, government policies significantly affect public emotions. Second, mediators should be related to the dependent variable. Model 2 in Table 8 demonstrates significant relationships between emotions (*Fear, Surprise*) and the reproduction number, supporting H2. Third, the effect of the independent variable on the dependent variable should be nonsignificant or attenuated when mediators are included in the regression and the bootstrapped confidence interval around the indirect effect should not include zero (Zhao et al. 2010).

Table 3. Means, standard deviations and correlation.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Reproduction number																		
2. Anger	0.05																	
3. Disgust	−0.07*	0.24***																
4. Fear	0.17***	0.15***	0.01															
5. Joy	−0.08**	−0.16***	−0.16***	−0.44***														
6. Sadness	0.004	0.12***	0.14***	−0.03	−0.07*													
7. Surprise	0.13***	−0.12***	0.07	−0.08**	−0.12***	0.21***												
8. Trust	−0.05	−0.23***	−0.11***	−0.30***	−0.57***	−0.18***	−0.19***											
9. Anticipation	−0.99	0.000	0.17***	−0.06	−0.09**	0.10**	0.29***	−0.16***										
10. Containment policy	−0.48***	−0.09**	−0.01	−0.13***	−0.000	−0.03	−0.07*	0.14***	0.04									
11. Economic policy	−0.36***	−0.11***	−0.004	−0.09**	−0.05	0.02	0.01	0.13***	0.03	0.66***								
12. Health policy	−0.36***	0.05	0.09**	0.02	0.06	−0.04	−0.13***	−0.05	−0.05	0.08**	0.11***							
13. Vaccination policy	−0.17***	0.14***	0.17***	0.09**	0.05	0.01	−0.12***	−0.13***	−0.03	−0.36***	-0.37***	0.68***						
14. Variant stage	−0.16***	0.12***	0.10***	0.09**	0.05	−0.01	−0.13***	−0.12***	−0.03	−0.36***	−0.33***	0.69***	0.96***					
15. Average policy strictness	−0.56***	0.02	0.09**	−0.02	0.02	0.001	−0.13***	0.02	−0.004	0.46***	0.54***	0.78***	0.53***	0.52***				
16. Mobility trends for grocery and pharmacy	0.20***	0.09**	0.07	0.08**	0.05	−0.003	−0.01	−0.14***	−0.03	−0.63***	−0.31***	0.34***	0.52***	0.57***	0.06			
17. Mobility trends for public transport hubs	0.40***	0.07	0.02	0.14***	0.01	0.003	0.06	−0.15***	−0.07	−0.81***	−0.37***	0.12***	0.26***	0.29***	−0.27***	0.71***		
18. Mobility trends for residential areas	−0.32***	−0.09**	−0.03	−0.08***	0.01	−0.02	−0.41	0.15***	0.08**	0.59***	0.39***	−0.25***	−0.34***	−0.39***	0.14***	−0.57***	−0.87***	
Max	5.26	1	1	1	1	1	1	1	1	86.46	100	76.39	100	6	90.71	51.47	5.80	31.63
Min	0.49	0	0	0	0	0	0	0	0	0	0	22.22	0	1	5.56	−90.43	−79.95	−1.65
Mean	1.10	0.18	0.10	0.47	0.41	0.17	0.12	0.37	0.18	56.44	83.82	65.42	46.66	3.29	63.08	−4.24	−33.89	11.03
Std. Dev.	0.34	0.12	0.11	0.13	0.14	0.10	0.07	0.10	0.11	19.15	32.10	11.96	41.19	1.79	14.83	14.92	16.42	6.82

N = 703.

*p < .1 **p < .05, ***p < .01.

Table 4. Hypothesis testing model for containment policy.

	Model 1.1 (M)								Model 1.3 (Y)	
Variables	Anger	Disgust	Fear	Joy	Sadness	Surprise	Trust	Anticipation	Y-X	Y-X+M
Control variables										
Variant stage	0.043*	−0.001	0.003	0.015**	−0.030	−0.069***	−0.009**	−0.026	−0.025**	
	(0.024)	(0.036)	(0.006)	(0.007)	(0.026)	(0.025)	(0.005)	(0.027)	(0.003)	
Average policy strictness	−0.000	0.005	0.001	−0.002**	0.004	0.004	0.000	0.002	−0.007***	
	(0.003)	(0.004)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	
Mobility trends for grocery and pharmacy	0.000	0.004	−0.001	0.000	−0.001	0.001	−0.000	0.001	0.006***	
	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)	(0.002)	(0.001)	
Mobility trends for public transport hubs	−0.002	−0.003	0.001	0.001	−0.004	0.001	−0.001	0.000	−0.006***	
	(0.004)	(0.006)	(0.001)	(0.001)	(0.004)	(0.004)	(0.001)	(0.004)	(0.002)	
Mobility trends for residential areas	−0.004	−0.004	−0.003	0.002	−0.002	0.007	0.000	0.012	−0.013***	
	(0.006)	(0.010)	(0.002)	(0.002)	(0.007)	(0.007)	(0.001)	(0.007)	(0.003)	
Independent variable										
Containment policy	0.001	0.000	0.000	0.001	−0.006**	−0.003	−0.000	−0.002	−0.003**	
	(0.003)	(0.004)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.001)	
R^2	0.021	0.012	0.040	0.015	0.007	0.029	0.036	0.021	0.233	

Y, reproduction number; X, containment policy; M, emotions. Standard errors are reported in parentheses.
*$p < .1$ **$p < .05$, ***$p < .01$.

Table 5. Hypothesis testing model for economic policy.

	Model 1.1 (M)								Model 1.3 (Y)	
Variables	Anger	Disgust	Fear	Joy	Sadness	Surprise	Trust	Anticipation	Y-X	Y-X+M
Control variables										
Variant stage	−0.022	−0.036	0.000	−0.004	0.031	0.000	0.003	0.023	0.039***	0.039***
	(0.031)	(0.046)	(0.007)	(0.009)	(0.033)	(0.032)	(0.006)	(0.034)	(0.012)	(0.011)
Average policy strictness	0.008	0.010	0.001	0.001	−0.004	−0.005	0.001*	−0.004	−0.012***	−0.012***
	(0.004)	(0.006)	(0.001)	(0.001)	(0.004)	(0.004)	(0.001)	(0.004)	(0.002)	(0.002)
Mobility trends for grocery and pharmacy	0.001	0.004	−0.001	0.001	−0.001	0.001	−0.000	0.000	0.004***	0.004***
	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)	(0.002)	(0.001)	(0.001)
Mobility trends for public transport hubs	−0.001	−0.003	0.000	0.001	−0.001	0.002	−0.001	0.001	−0.003***	−0.003***
	(0.003)	(0.005)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.004)	(0.001)	(0.001)
Mobility trends for residential areas	−0.004	−0.003	−0.003*	0.002	0.001	0.008	0.000	0.013*	−0.009***	−0.009***
	(0.006)	(0.009)	(0.002)	(0.002)	(0.007)	(0.006)	(0.001)	(0.007)	(0.002)	(0.002)
Independent variable										
Economic policy	0.183*	−0.098	−0.005	−0.037*	0.080	−0.156**	0.030**	0.112	−0.1316***	−0.1269***
	(0.077)	(0.116)	(0.019)	(0.022)	(0.082)	(0.080)	(0.015)	(0.085)	(0.029)	(0.029)
Mediators										
Surprise										0.0309**
										(0.014)
R^2	0.030	0.013	0.040	0.017	0.003	0.033	0.041	0.023	0.252	0.256

Y, reproduction number; X, economic policy; M, emotions. Standard errors are reported in parentheses.
*$p < .1$ **$p < .05$, ***$p < .01$.

Table 6. Hypothesis testing model for health policy.

	Model 1.1 (M)								Model 1.3 (Y)	
Variables	Anger	Disgust	Fear	Joy	Sadness	Surprise	Trust	Anticipation	Y-X	Y-X+M
Control variables										
Variant stage	0.041*	−0.002	0.003	0.007	0.013	(.018)	−0.007**	−.009	−0.001	−0.000
	(0.018)	(0.027)	(0.004)	(0.005)	(0.019)		(0.003)	(.020)	(0.007)	(0.007)
Average policy strictness	0.002	0.006*	0.002***	−0.002***	0.004	.004	0.000	.003	−0.004***	−0.004***
	(0.003)	(0.004)	(0.001)	(0.001)	(0.003)	(.003)	(0.001)	(.003)		(0.001)
Mobility trends for grocery and pharmacy	0.000	0.004	−0.001	0.000	−0.001	.001	−0.000	.001	0.004***	0.004***
	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(.002)	(0.000)	(.002)	(0.001)	(0.001)
Mobility trends for public transport hubs	−0.003	−0.004	0.000	0.000	0.000	.003	−0.000	.002	−0.002	−0.002
	(0.003)	(0.005)	(0.001)	(0.001)	(0.003)	(.003)	(0.001)	(.004)	(0.001)	(0.001)
Mobility trends for residential areas	−0.006	−0.004	−0.003**	0.002	−0.002	.007	0.000	(.007)	−0.010***	−0.010***
	(0.006)	(0.010)	(0.002)	(0.002)	(0.007)	(.007)	(0.001)		(0.002)	(0.002)
Independent variable										
Health policy	−0.146	−0.090	−0.075**	0.087**	−0.412**	−.174	0.007	−.242	−0.2547***	−0.2464*
	(0.155)	(0.234)	(0.037)	(0.044)	(0.164)	(.161)	(0.029)	(.171)	(0.058)	(0.058)
Mediators										
Fear										0.116*
										(0.074)
R^2	0.022	0.012	0.046	0.018	0.011	.029	0.035	.023	0.252	0.255

Y, reproduction number; X, health policy; M, emotions. Standard errors are reported in parentheses.
*$p < .1$ **$p < .05$, ***$p < .01$.

Table 7. Hypothesis testing model for vaccination policy.

	Model 1.1 (M)								Model 1.3 (Y)	
Variables	Anger	Disgust	Fear	Joy	Sadness	Surprise	Trust	Anticipation	Y-X	Y-X+M
Control variables										
Variant stage	−0.066*	−0.066	−0.007	0.007	−0.041	−.016	0.006	−.001	0.016	
	(0.039)	(0.060)	(0.011)	(0.011)	(0.042)	(.041)	(0.007)	(.002)	(0.017)	
Average policy strictness	−0.001	0.005	0.001	−0.001*	−0.001	.002	0.000	.004	−0.008***	
	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(.002)	(0.000)	(.044)	(0.001)	
Mobility trends for grocery and pharmacy	0.001	0.005	−0.001	0.000	−0.001	.001	−0.000	.001	0.006***	
	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(.002)	(0.000)	(.003)	(0.001)	
Mobility trends for public transport hubs	−0.004	−0.004	0.000	0.000	−0.001	.004	−0.000	.001	−0.004***	
	(0.003)	(0.005)	(0.001)	(0.001)	(0.003)	(.003)	(0.001)	(.003)	(0.001)	
Mobility trends for residential areas	−0.007	−0.005	−0.003**	0.002	−0.000	.009	0.001	.002	−0.011***	
	(0.006)	(0.010)	(0.002)	(0.002)	(0.007)	(.007)	(0.001)	(.004)	(0.003)	
Independent variable										
Vaccination policy	0.005***	0.003	0.000	0.000	0.002	−.002	−0.001**	−.001	−0.001*	
	(0.002)	(0.002)	(0.000)	(0.000)	(0.002)	(.002)	(0.000)	(.002)	(0.001)	
R^2	0.034	0.014	0.042	0.012	0.004	.029	0.041	.020	0.229	

Y, reproduction number; X, vaccination policy; M, emotions. Standard errors are reported in parentheses.
*$p < .1$ **$p < .05$, ***$p < .01$.

Table 8. Hypothesis testing 2.

	Model 2
Control variables	
Variant stage	−0.003
	(0.007)
Average policy strictness	0.007***
	(0.001)
Mobility trends for grocery and pharmacy	0.004***
	(0.001)
Mobility trends for public transport hubs	−0.002***
	(0.001)
Mobility trends for residential areas	−0.009***
	(0.002)
Mediators	
Anger	0.026
	(0.024)
Disgust	−0.008
	(0.012)
Fear	0.364*
	(0.213)
Joy	0.274
	(0.259)
Sadness	0.018
	(0.017)
Surprise	0.051**
	(0.023)
Trust	0.326
	(0.354)
Anticipation	0.018
	(0.018)
R^2	0.215

Standard errors are reported in parentheses.
*$p < .1$ **$p < .05$, ***$p < .01$.

Table 9. Main components in mediation models.

	Model 1.3	Model 2.3	Model 3.3	Model 4.3
Independent variable	Containment policy	Economic policy	Health policy	Vaccination policy
Mediating variables		Surprise	Fear	

Dependent variable is reproduction number for all models.

Based on the results from the first two steps, containment policy is related to *Sadness*, which is not significantly related to the reproduction number. Hence, H3a is not supported. Following this logic, two mediation models, Model 2.3 and Model 3.3 in Table 9, are established. To test H3b, Model 2.3 in Table 5 shows that when both the economic policy and the emotion *Surprise* are included, *Surprise* has a positive influence on the reproduction number. Additionally, the effect of economic policy on the reproduction number becomes attenuated, changing from 0.00282 to 0.00275. Furthermore, Model 2.3 in Table 10 indicates that the mediating effect is significant, as the bootstrapped confidence interval around the indirect effect does not include zero [95% CI$(1.0 \times 10^{-5} - 2.2 \times 10^{-4})$]. Thus, H3b is supported. In testing H3c, when both the health policy and the emotion *Fear* are included, Model 3.3 in Table 6 presents that *Fear* has a positive influence on the reproduction number. Additionally, the effect of health policy on

Table 10. Tests of indirect effects.

	95% CI Economic policy (Model 2.3)		95% CI Health policy (Model 3.3)	
Mediators	Lower	Upper	Lower	Upper
Fear			-4.8×10^{-4}	-1.0×10^{-5}
Surprise	1.0×10^{-5}	2.2×10^{-4}		

Results are based on 5,000 bootstrap samples. CI, confidence interval.

the reproduction number becomes attenuated, changing from 0.0065 to 0.0063. Moreover, Model 3.3 in Table 10 shows that the mediating effect is significant, since the bootstrapped confidence interval of the indirect effect does not include zero [95% CI(-4.8×10^{-4} – -1.0×10^{-5})]. Thus, H3c is supported. Lastly, H3d is not supported, because *Anger* and *Trust* are not significantly related to the reproduction number.

To better understand the importance of emotions' mediating effects, the proportion mediated is utilized to quantify the extent to which the exposure's effect on the outcome is attributable to its impact on the intermediary variable (Miočević et al. 2018). Based on the decision tree of mediation types (Preacher and Hayes 2008; Zhao et al. 2010), it has been discovered that *Surprise* and *Fear* demonstrate complementary mediation effects of 3.6% and 3.25%, respectively, on economic policy and health policy. These findings indicate that both the direct path (c') and the indirect path (a × b) depicted in Figure 6 operate in the same direction, contributing to a greater reduction in the reproduction number when economic and health policies are stricter. In other words, heightened stringency in economic and health policies results in not only a direct reduction in the reproduction number but also an indirect reduction through the decrease in *Surprise* and *Fear*. To better elucidate this mechanism, we present an illustrative example extracted from a randomly selected user from our dataset who expressed personal perspectives through the following tweet: '*I would not wear a face mask if you were so scared to go out, because the face mask will not save you from COVID. The scientists are saying the affordable face masks are useless*'. This example emphasizes our central theme, namely, that individuals' emotional reactions to government policy announcements are a critical determinant in pandemic management.

Supplementary analysis

To substantiate the model's robustness, supplementary analysis is undertaken. First, the Kolmogorov-Smirnov normality test because the sample size is larger than 50 (Jr and Frank 1951). K-S statistic in Table 11 shows that the reproduction number, emotions and policies are all significant ($p < 0.05$), implying a non-normal distribution. To resolve this, we apply Hayes's bootstrap method (Marie and Lin 2016). Second, an alternative model incorporating additional control variables in Table 12, including mobility trends in workplaces, parks, retail and recreation, is estimated. The consistent pattern of results reinforces the key findings presented earlier, increasing the overall confidence in the generalizability of our study.

Table 11. Normality test.

	K-S statistic
Reproduction number	0.73**
Anger	0.50**
Disgust	0.50**
Fear	0.58**
Joy	0.54**
Sadness	0.50**
Surprise	0.50**
Trust	0.55**
Anticipation	0.50**
Containment policy	0.97**
Economic policy	0.97**
Health policy	1.00**
Vaccination policy	0.60**

$^{*}p < .1$ $^{**}p < .05$, $^{***}p < .01$.

Table 12. Robustness check.

	Coefficient	Standard Error	Lower CI	Upper CI
Mediation model 1				
X_e ➔ Surprise	−0.0004**	0.0002	0.0001	.0007
Surprise ➔ Y	0.281**	0.136	0.057	.506
Total effect	−0.0400***	0.0006	0.0026	.0046
Direct effect	−0.0350***	0.0006	0.0025	.0045
Indirect effect	−0.0005***	0.0001	**0.0000**	.0002
Mediation model 2				
X_h ➔ Fear	−0.002**	0.0009	−0.0034	−.0006
Fear ➔ Y	0.116*	0.068	0.005	.228
Total effect	−0.0102***	0.0014	−0.0126	−.0080
Direct effect	−0.0101	0.0014	−0.0124	−.0078
Indirect effect	−0.0001	0.0001	**−0.0005**	−.0000

Y, reproduction number; X_e, economic policy; X_h, health policy; M, emotions. CI, confidence interval.
$^{*}p < .1$ $^{**}p < .05$, $^{***}p < .01$.

Discussion and conclusion

The main objective of this paper was to explore the underlying dynamics of public emotions in managing the relationship between government policies and their management performance in the context of the COVID-19 crisis in the UK. In alignment with prior studies (Liu, Shahab, and Hoque 2022; Renström and Bäck 2021), it appears that public emotions potentially have diverse effects on individuals' political decision-making by influencing the performance of political events. This answers the call of comprehensively analysing emotion components, instead of general sentiment polarity, in crisis messaging, which is a critical subject in public management field (Han and Baird 2022). Importantly, our findings suggest the plausible involvement of emotions, particularly fear and surprise, serving as mediators within the context of government policies and their consequential outcomes in pandemic management. This highlights the importance of gaining a more nuanced understanding of emotions in the context of public health crisis. Overall, our study contributes to the broader field of public management by extracting management value from emotional signals within social media messages and providing valuable insights into the control of infectious diseases, ultimately mitigating their impact on the public health system and society (Han and Baird 2022; Zheng, Hongxia, and Sun 2021).

Theoretical contributions

First, our results validate AIT by revealing that emotions, serving as fundamental drivers of policy support, exert an influence on policy effectiveness through mediating mechanisms. Additionally, the divergent patterns identified in these mechanisms could potentially contribute to enriching and further refining the interpretation of the theory. They suggest the potential significance of conducting a systematic and nuanced exploration of emotion components, which may be intricately linked to the citizen-government relationship within distinct policy settings (Smith and Huntsman 1997). For containment and vaccination policies, people feel powerless, as their acceptance of such policies stems from the government's absolute authority and technical expertise, factors that lie beyond their personal control (da Silva, Sguera, and Story 2022). Particularly, containment policies, such as the closure of schools or workplaces, impose limitations on individuals' mobility, while the development of vaccines remains within the purview of professionals. In such scenarios, regardless of the emotions elicited by the surveillance or disposition system, ordinary citizens may find themselves compelled to align their behaviours with emerging moral principles, nullifying the potential mediating effects. However, individuals possess greater autonomy and freedom in deciding whether to accept financial assistance offered through economic policies and adhering to preventive advice provided by health policies; emotional engagements fluctuate accordingly, potentially exerting further influence on pandemic management performance (da Silva, Sguera, and Story 2022). Hence, our study adds to a more thorough understanding of the interaction between government policies and citizens in the context of public health crisis management, particularly by elucidating the nuanced roles of emotions (Han and Baird 2022).

Second, our study contributes to strengthening findings that even emotions of the same polarity (either positive or negative) can influence public policy implementation performance differently, owing to the diverse nature of associated behaviours (Rodriguez-Sanchez et al. 2018). Scholars have discussed this discrepancy by proposing that emotions of same polarity do not inherently equate to being universally 'good' or 'bad' in varying policy contexts. Rather, depending on the risk associated with a certain threat, they can result in markedly divergent assessments of an event, exerting diverse impacts on matters such as the implementation result of public policies (Gaspar et al. 2016; Liu, Shahab, and Hoque 2022). This explanation is supported by one of our findings that the negative emotion (*Fear*) can mediate the relationship between health policy and pandemic management performance, whereas it loses this function under other types of policies. It is observed that risk-averse behaviour is frequently caused by the emotion of fear, which is produced by uncertainty (Trepel, Fox, and Poldrack 2005). Compared with health policies, containment policies mainly aimed to restrict people's movement, involving numerous constraints rather than excessive uncertainty. Economic policies, designed to assist individuals facing financial challenges, offer more immediate relief compared to measures implemented through health policies; thus, these rapid and straightforward adjustments reduce uncertainty and diminish the likelihood of instilling fear. Additionally, Lerner and Keltner (2001) indicate that risk-seeking behaviours are frequently caused by the emotion of anger, helping to explain the absence of fear in regard to vaccination policies. Specifically, the essence of vaccination policies lies in promoting risk-seeking behaviours of accepting a novel vaccine; thus, the emotion that best characterizes this scenario is anger, rather than fear, which also aligns with our findings. Overall, our study enriches the emerging research stream that investigates the role of public emotions in pandemic policy implementation with a more comprehensive vision, which can serve as a valuable inspiration for future research, aiming to reveal potential incentives hidden behind the same emotional expression.

Third, our study bears meaningful implications on public policy and public management literatures, as it contributes to the public policy management model by optimizing its last step, policy evaluation. The public policy management model is a solid framework that provides clear guidance for policymakers by integrating public management philosophy into the process of identifying, analysing, and managing public issues (Jones and Howard Chase 1979). As Bryson, George, and Seo (2022) observed, emotions would guide goal-directed efforts to be more effectively materialized while evaluating the goal; thus, being equipped with strategic information on the emotivity of public policy issues allows policymakers to strengthen ongoing policies and be resilient in terms of public management (Ansell, Sørensen, and Torfing 2021). Moreover, as the European Centre for Disease Prevention and Control urges, evidence-based information is required to bridge the gap between science, policy, and practice, allowing a more effective evaluation of public health policies (European Centre for Disease Prevention and Control 2021). Considering these calls, our study reveals emotion's potential to aid in the optimization of policy evaluation. Particularly, the evaluation of economic and health policies may consider emotional variables, as emotions clarify the intended and actual policy outcomes through mediating mechanisms, thereby increasing precision in the evaluation process. Besides, containment policies should prioritize high-quality data collection over emotions, because the imposition of restrictive measures created suboptimal conditions for obtaining feedbacks about these policies and therefore need to be further assessed to establish a thorough and long-term perspective evaluation system (William and Stéphan 2021).

Policy implications

Our findings also have several valuable policy implications. First, the paper provides insightful recommendations for improving public health rapid response capacity, a crucial aspect in curtailing viral transmission (Zheng, Hongxia, and Sun 2021). Considering reproduction number calculation is subject to time delays, limiting its ability to reflect the real-time dynamics of the pandemic (Zhou et al. 2020), it is recommended that UK policymakers, who faced criticism for delays during the early phases of the pandemic, proactively monitor anomalous fluctuations in public emotions on social media platforms to identify early warning signs and undertake appropriate measures. Tracking emotions can serve as an agile auxiliary to minimize time expenditure, thus bolstering the effectiveness of public health rapid response capacity (Lai 2018). Because socio-economic measures often involve lengthy and rigid bureaucratic procedures, traditional policy processes is time-consuming and ill-suited to urgent situations (Capano 2020). By tracking and analysing emotions, policymakers gain valuable insights into emotional concerns of the population. This additional information, when incorporated into the initiation of policy formulation, enables policymakers to align response strategies with the prevailing public emotions, securing policy compliance and then effectiveness of pandemic management. Also, the real-time nature of tracking emotions empowers policymakers to swiftly identify emerging issues, rapidly adjust their policy approaches, and seize timely intervention opportunities, consequently cultivating responsiveness to evolving circumstances and mitigating implementation delays. Moreover, it provides a nuanced understanding of the societal response to proposed policies, identifying potential areas of public resistance. For example, anger as an emotion can instigate social riots as a resistance to lockdown measures (Ansell, Sørensen, and Torfing 2021). Being cognizant of this emotional signal, policymakers can proactively refine their policy options to avoid undesirable social disorders, reducing the risk of investing substantial time and resources into policies that may ultimately face significant public opposition.

Second, our study underscores the importance of incorporating the tracking of public emotions alongside the reproduction number to attain heightened efficacy in viral infection control. This approach plays a vital role in alerting government officials to challenging situations, thereby facilitating efforts in viral control. Based on our findings and the observed decrease in the reproduction number in the UK, which exhibited a decline of 84% from approximately 5 in March 2020 to 0.8 in May 2022 (GOV.UK 2022), it is revealed that a one-standard-deviation decrease in *Fear* (i.e. a 0.213 decrease in Table 9) leads to an estimated 8% reduction in the reproduction number. Applying this framework to the UK context, we anticipate an additional 6.7% reduction in the reproduction number upon successful fear mitigation. This implies that, for every 1,000 infected cases, approximately 67 fewer individuals would contract the infection following a one-standard-deviation decrease in fear. Inspired by this and insights into the mediating effects of emotions, we recommend deploying a sentiment engine for real-time emotion monitoring in the context of public health policy formulation. This approach transcends the limitations of solely tracking the reproduction number and provides a more efficient mechanism for notifying policymakers of critical situations. For instance, when a certain emotion score exceeds a predefined threshold, it signals an uncontrollable and highly frequent virus transmission. Subsequently, policymakers can explore the root causes of this unsatisfaction and prioritize the mitigation of tensions stemming from threshold-crossing emotions. These actions, undertaken by policymakers who recognize the connection between threshold-crossing emotions and uncontrollable viral transmission, not only contribute to the establishment of trust and cooperation between the government and the public but also create an environment conducive to successful public management by promoting greater levels of policy compliance. As a result, they significantly contribute to enhancing viral control.

Third, our findings provide empirical evidence supporting the streamlining of pandemic management policy design (Newman, Cherney, and Head 2017). Policymakers are recommended to adopt an evidence-based approach to policy design by carefully considering the multifaceted role of public emotions. Understanding how and for which policies emotions matter is critical to the success of public policies (Durnová and Hejzlarová 2018). By capturing the subjective experiences, concerns, and motivations of the public, emotional signals can provide complementary evidence, resulting in more targeted policies for strengthening the overall policy design process. Notably, the poor pandemic management, along with social chaos, during the early stages of the pandemic in Italy, is an emblematic example of incoherently designed policies (Capano 2020). This underscores the importance of policy formulators basing their decisions on evidence-based information, as it constitutes an indispensable components of efficient policy design (Newman, Cherney, and Head 2017). Given this imperative, we strongly recommend that policymakers incorporate evidence-based information on the varied roles of public emotions into policy design. In particular, policymakers designing containment and vaccination policies should prioritize the relationship between policy and its performance because, without emotions' mediating mechanism, the stricter these policies are, the greater the influence they have on promoting a desirable outcome in pandemic control. However, identical recommendations cannot be extended to economic and health policymakers, because their contributions to the pandemic management performance are also subject to the influence of emotions such as fear and surprise. This highlights the importance of balancing policy stringency to mitigate unmanageable emotional responses, which have the potential to detrimentally impact policy compliance and the overarching management of the pandemic. Overall, our study contributes to the systematic and granular examination of policy designs by encouraging a more comprehensive understanding of the societal context in which policies are to be implemented.

Limitations and future research

We acknowledge several limitations. First, we are unable to differentiate between hidden sources of the same emotion. Fear acts as a mediating factor between health policies and pandemic management performance, but it does not exert a similar influence on other policies. Future research could explore the reasons behind this inconsistency using natural language processing methods. Secondly, while Twitter has been relatively impartial and sufficiently general, there is a possibility of bias in our findings due to its exclusive use as the data source. Exploring data from other social media platforms may reveal variations in the mediating effects of emotions, offering an intriguing avenue for further investigation. Thirdly, future studies should focus on developing a comprehensive epidemiological parameter designed to evaluate governments' performance in pandemic management, which should encompass all the relevant nuances involved in assessing government responses to public health crises. Fourth, given the multifaceted nature of emotions and their potential interactions with diverse contextual factors, we encourage future research to investigate the dynamics of public emotions in political activity performance across a wider range of research contexts, contributing to a more comprehensive understanding of the complexities at play in this domain.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendixes

Appendix 1. Explanation of Key Variable Measurement

We offer more details regarding the meaning of our data is essential to make our work more readable and understandable.

Policy stringency comes from the Oxford COVID-19 Government Response Tracker (OxCGRT) which is the project designed and developed by the Blavatnik School of Government, University of Oxford. It systematically collects information on several different common policy responses governments have taken, records these policies on a scale to reflect the extent of government action, and aggregates these scores into a suite of policy indices. Furthermore, the data has been collected and reviewed by a team that has comprised more than 400 volunteers from Oxford University and partners, ensuring its reliability (Hale et al. 2021).

By definition, policy stringency denotes the degree of mandatory compliance associated with the implementation of a given policy. In particular, there are 8 sub-indicators describing containment policy; 4 sub-indicators describing economic policy; 8 sub-indicators describing health policy; 3 sub-indicators describing vaccination policy. For each type of policy, an overall policy stringency is calculated using corresponding sub-indicators. For containment policy, for example, school closure is a sub-indicator describing the policy and presented in an ordinal scale:

(1) 0 - no measures
(2) 1 - recommend closing or all schools open with alterations resulting in significant differences compared to non-Covid-19 operations
(3) 2 - require closing (only some levels or categories, e.g. just high school, or just public schools)
(4) 3 - require closing all levels

Based on that, the policy stringency for school closure ranges from 0 to 3, indicating the level of mandatory compliance required from the population during its implementation. Considering different sub-indicators may have different scales, the Equation 3, derived from the OxCGRT, is used for normalising these different ordinal scales to produce a score between 0 and 100 where each full point on the ordinal scale is equally spaced. In doing so, containment policy averages its 8 sub-indicator scores to get an overall policy stringency for containment policy. Similar patterns are applied to the rest of policies. Additionally, we offered the github link for Equation 3, as follow: https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/index_methodology.md.