The Factors Influencing the Effectiveness of Policy Implementation: Insights from Social Media Analysis during the COVID-19 Crisis in the UK

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Abstract

In the era of social media, the effective implementation of governmental policies has become increasingly crucial for achieving desired outcomes and addressing societal issues. Public discourse surrounding these policies often generate negative and misleading influences that can hinder their successful execution. A lack of understanding of the factors that drive policy success undermines policymakers' ability to design effective interventions for managing public events. Therefore, this thesis aims to investigate the dynamics influencing the implementation performance of policies, contributing not only to the academic literature but also offering practical implications for enhancing public welfare and the efficacy of governmental policies.

The central research question focuses on exploring the factors that influence the effectiveness of policy implementation. Utilizing data mining techniques, the thesis extracts 144K Twitter posts from the United Kingdom and employs research methods, including regression analysis, machine learning, and text data analysis, to comprehensively examine the underlying dynamics.

Consequently, this thesis has discovered that minimizing certain public emotions can enhance policy effectiveness, thereby facilitating improved implementation outcomes. Besides, the thesis advises policymakers that increasing the volume of detailed descriptions of protective behaviours and implementing strategies aimed at cultivating public trust can reduce misinformation about government policies. Furthermore, the thesis reveals the diverse impacts of risk perceptions on policy implementation performance, suggesting that risks perceived at individual, group, and societal levels should be addressed differently to achieve optimal policy implementation outcomes.

Overall, this thesis makes a significant theoretical contribution through a novel investigation of the impact of public emotions and varying risk perceptions on policy performance, which enriches the existing literature in information systems, public management, and social media data analysis. Moreover, this thesis advocates for implementing more targeted measures for managing misinformation, providing practical implications that aid policymakers in navigating challenges and enhancing management effectiveness during similar crisis scenarios in the future.

Acknowledgements

First, I would like to express my profound gratitude to my supervisors: Dr. Maged Ali, Professor Niraj Kumar, and Dr. Wen Zhang, as well as my panel board chairs: Professor Ramakrishnan Ramanathan and Dr. Debabrata Ghosh. I also extend my heartfelt thanks to all the colleagues who generously assisted me throughout my research journey.

I am deeply appreciative of the University of Essex, particularly the staff at EBS Southend, for their unwavering support during my PhD studies. My sincere thanks also go to my friends and fellow PhD colleagues for their warm camaraderie and encouragement. To them, I say: there is light at the end of the tunnel!

Finally, I owe my endless gratitude to my family. This thesis would not have been possible without their unconditional love and support. Thank you for your continuous encouragement and for enduring this long process with me.

List of Publications

The following publications have resulted from the work contained in this thesis at the time of submission. It should be noted that there are two other papers currently under different stages of the publication process.

- Lu, M., Ali, M., Zhang, W. and Kumar, N., 2023. Mediation analysis of public emotions in response to policy implementation performance during crises: the case of COVID-19 management policies in the UK. *Public Management Review*, pp.1-32.
- Lu, M., Ali, M., Kumar, N. and Zhang, W., 2023. Identification of the impact of content related factors on the diffusion of misinformation: A Case study of the government intervention policies during COVID- 19 pandemic in the UK. *Americas Conference on Information Systems (AMCIS),* Panama City, Panama.
- Lu, M., Ali, M., Kumar, N. and Zhang, W., 2024. The Impact of Misinformation on Government Policy Performance: Moderating Effects through Public Risk Perception. *2024 INFORMS Annual Meeting*, Seattle, US.

Table of Contents

List of Figures

List of Tables

List of Formulae

List of Abbreviations

AIT	Affective Intelligence Theory
OxCGRT	Oxford Covid-19 Government Response Tracker
API	Application Programming Interface
WHO	World Health Organization
ELM	Elaboration Likelihood Model
LDA	Latent Dirichlet Allocation
BoW	Bag-of-Words
NHS	National Health Service
TWRC	Two-Way Risk Communication
PMT	Protection Motivation Theory
OLS	Ordinary Least Squares
GIFS	Google Insights for Search
SDOH	Social Determinants of Health

Chapter 1. Introduction

1.1 Background and Research Rationale

As the unprecedented health crisis has disrupted the lives of millions over the past three years, governments worldwide have been challenged not only by the spread of the virus itself but also by the inefficiency of management policies in this situation (Kweon & Choi, 2023). It has been observed that numerous individuals exhibit reluctance to accept and adhere to these policy guidelines, perceiving them as substantial disruptions to their daily routines (Coroiu, Moran, Campbell, & Geller, 2020). The implementation of these novel policies has resulted in significant disruptions to both professional and personal aspects of individuals' lives, resulting in emotional reactions to these abrupt changes (Reuter & Kaufhold, 2018). Furthermore, in the contemporary information-driven society, misinformation concerning health outbreaks and the associated government measures proliferates extensively across social media platforms (Dwivedi et al., 2020). This proliferation of misinformation further undermines public willingness to comply with the guidelines established by policymakers. In fact, these phenomena are fundamentally rooted in the public's perception of the potential risks associated with the situation, ultimately impacting the effectiveness of policy implementation (Dedeoğlu & Boğan, 2021). Indeed, the proficient execution of government policies, taking into account public attributes, is widely acknowledged as an indispensable imperative. This research perspective not only fosters the development of robust governance structures but also strengthens the provision of public services while ensuring the optimal utilization of resources (Farooqi & Forbes, 2020). So, this thesis conducts a comprehensive examination of government policy implementation with a focus on public attributes, which will serve as a valuable mechanism for uncovering operational inefficiencies and identifying critical bottlenecks, particularly in times of crises.

1.2 Research Gap and Objectives

Recent studies examining the influential factors of policy performance predominantly encompass considerations related to government actions, as well as those independent of such actions. Within the domain of factors pertinent to government actions as perceived by policymakers, primary considerations include policy portfolios, covering elements such as policy targets and instruments (Fernández‐i‐Marín, Hinterleitner, Knill, & Steinebach, 2023), alongside administrative committees characterized by attributes including board independence, size, diversity, as well as the nature of the regime and prevailing political ideologies (Reddy, Locke, & Scrimgeour, 2011; Voets, Van Dooren, & De Rynck, 2008). Regarding factors unrelated to government actions, in addition to the features inherent in the processing of implementation policies, such as legitimacy, accountability, and accordance (Voets et al., 2008), and contextual factors, including technological improvements and economic freedom (Fernández‐i‐Marín et al., 2023; Gropper, Jahera Jr, & Park, 2015), one of the most significant elements under investigation concerns how the public responds to policies. Relevant literature underscores that public responses are pivotal factors in ensuring the effective policy implementation. Public reactions, often diverging from government expectations, can precipitate emotional responses (Reuter & Kaufhold, 2018). These reactions, in turn, may compromise policy efficacy by propagating misinformation, which distorts perceptions of risk (Shahbazi & Bunker, 2024). Misinformation can amplify uncertainties and lead to divergent interpretations of potential risks, undermining rational decision-making (Wamsler et al., 2023). This not only complicates public health responses but also erodes trust in authoritative information, exacerbating societal polarization and hindering collective efforts to address real and perceived threats effectively. Therefore, these dynamics pose significant challenges to policy performance, especially during the COIVD-19 time period. Given the absence of research examining the perspective of general public attributes, this thesis delves into the utilization of social media text data by employing advanced business analytics techniques to analyse the factors shaping effective COVID-19 management policy implementation, aiming to uncover previously overlooked aspects essential for enhancing policy performance and refining public management strategies.

1.3 Research Questions

To investigate these matters, the thesis formed three research questions:

Q1. How does the stringency of the COVID-19 management policies influence public emotions, consequently impacting the effectiveness of policy implementation during the pandemic time?

Q2. What are the significant factors that contribute to the dissemination of misinformation regarding government policies during the COVID-19 time period?

Q3. How do perceptions of risk affect the relationship between misinformation and the COVID-19 management policy performance during the pandmeic time period?

1.4 Significance to Literature and Practice

The discoveries of this thesis hold the promise of empowering policymakers by furnishing them with a robust theoretical framework and facilitating the development of more tailored and sustainable policies that resonate with public attributes in real-world scenarios, ultimately, fostering policy resilience and community cohesion during challenging times.

Particularly, the findings support and enrich the public management literature by illustrating how public emotional responses, elicited by various government policies, exert influence on policy efficacy through mediating mechanisms (Marcus, Neuman, and MacKuen, 2000). The proposal of a sentiment engine, correlating fluctuations in public emotions with policy performance, offers a means of alerting policymakers to critical situations based on emotional shifts. This facilitates policymakers in prioritizing the fulfilment of the needs of populations experiencing heightened emotional distress, thereby mitigating widespread virus transmission. Moreover, the investigation into misinformation, viewed through the lens of information diffusion, has contributed to the advancement of information systems by revealing varied patterns in misinformation propagation. A distinctive contribution lies in the examination of social interaction dynamics, an aspect that contemporary theories in misinformation diffusion research have not fully addressed (Cyr et al., 2018; Feng et al., 2021). In addition, the identification of influential topics can inspire policymakers to implement effective strategies for mitigating misinformation, with potential applications extending to other fields in the future. Furthermore, this thesis not only offers valuable theoretical insights into the risk perception paradox, which investigates why individuals may be susceptible to misinformation's impact on policy implementation under certain conditions while demonstrating resilience against its influence in others (Wachinger et al., 2013), but also analyses risks at a more granular level. This advocacy has prompted policymakers and public health authorities to develop more nuanced and targeted risk communication strategies, necessitating consideration of the heterogeneous nature of the public's risk perception (Kellens et al., 2013).

1.5 Summary and structure of the thesis

In a word, based on research questions primarily focused on exploring the influential factors of policy performance, the thesis addresses a critical oversight by examining the gap that neglects the impact of public reaction on policy effectiveness. By hypothesizing the intricate relationships between COVID-19 management policies and public emotions, misinformation dissemination, and risk perceptions, this thesis investigates how novel government policies initially influence public emotions, which may in turn catalyze the spread of misinformed messages. Further, it examines how underlying risk or uncertainty perceptions can explain such occurrences and ultimately affect policy performance during the COVID-19 pandemic. A logic chart has been presented in Figure 1.1 to visually depict the linkage among the three topics in the following chapters.

Specifically, the thesis is structured as follows. Chapter 2 provides a more detailed illustration of the research approach and methodologies, creating a coherent narrative flow throughout the thesis. Chapter 3 uses mediation analysis and regression modelling methods to study the relationship between government policies and its performance through a mediation mechanism of public emotions Chapter 4 applies predictive modelling and topic modelling methods to uncover dynamics shaping misinformation from the Information System perspective and explored the potential influence of government policies on misinformation regarding the COVID-19 Chapter 5 utilizes text mining methods and regression modelling to uncover the impact of misinformation on policy implementation and examine how embedded risks and uncertainties within policy information serve to moderate its influence. Lastly, Chapter 6 presents the discussion and conclusion of the thesis. This chapter covers the main conclusions from the three papers that compose the thesis, emphasising their main theoretical and practical contributions, as well as it presents some limitations and recommendations for further research.

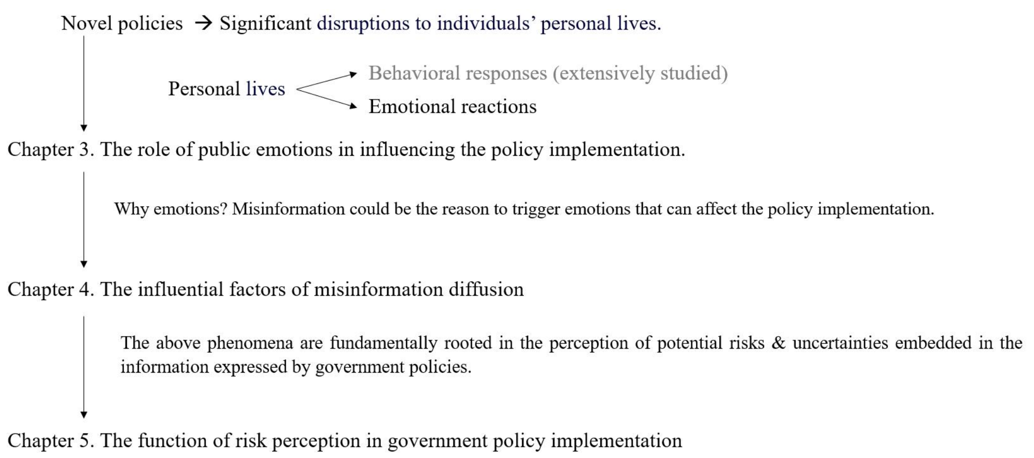


Figure 1.1 Logic Chart of the Thesis

Chapter 2. Research Approach and Methodology

2.1 Research Topics and Linkage

2.1.1 Paper Linkage

This section outlines the connections and relationships between the three paper chapters (Chapter 3, Chapter 4, and Chapter 5), highlighting how they are interconnected across different aspects of government policies, public emotions, misinformation, and policy implementation.

Chapter 3 establishes a valuable understanding by exploring how government policies influence their performance, with public emotions acting as a mediation mechanism. This chapter sets the stage by highlighting the complex interplay between policy formulation, public emotions, and policy outcomes. Building upon the insights gained from Chapter 3, Chapter 4 shifts focus to the dynamics shaping misinformation within information systems, particularly in the context of COVID-19. This chapter delves into the potential influence of government policies on the spread of misinformation. It thus extends the discussion of public emotions initiated in Chapter 3 by examining how policies, although intended to inform and guide, can inadvertently contribute to the dissemination of false or misleading information. Finally, Chapter 5 expands upon the narrative by examining the fundamental factors that influence policy implementation. It explores how inherent risks and uncertainties within policy information can affect people's interpretation and subsequent actions.

In summary, after examining the two most valuable topics discussed in Chapters 3 and 4, Chapter 5 further uncovers the underlying reasons behind these narratives and deepens the understanding of policy effectiveness, which offers a more profound interpretation of how the general public perceives potential risks and uncertainties associated with abrupt social events. This interconnection ensures a holistic view of the complex interactions between policies, public emotions, misinformation, risk perceptions, and their collective impact on societal outcomes.

2.1.2 Contributions to the Gap in Each Paper

This section highlights the key contributions of each paper in addressing the main research gap. Considering the significant role that various public attributes play in launching government policies, gaining a comprehensive and thorough understanding of these reactions serves as a valuable tool for uncovering operational inefficiencies and identifying crucial bottlenecks in the effective management of social events.

To address this significant gap, Chapter 3 (Paper 1) focuses on the emotional reactions of the general public. It explores people's emotions, which are often hidden and difficult to externalize in public discussions, and their potential influences on social events. Additionally, Chapter 4 (Paper 2) examines misleading messages, a prominent form of written expression that contributes to public attributes in the investigation of government policy implementation. Given their substantial negative impact on the formation of correct values among the general public, the exploration of this topic can assist policymakers in avoiding errors and leveraging public attributes more effectively to manage social events. Lastly, regardless of how these latent emotions or open dialogues affect policy performance, the central idea is to understand how underlying risks or uncertainties would shape people's perceptions of information received during social events. Chapter 5 (Paper 3) contributes to this gap by providing insights from a fundamental level of recognition, serving as a guiding principle that can be applied to other social events in the future.

2.1.3 Contributions Aligned with Research Questions in Each Paper

To present the thesis in a clear and more organized manner, this section provides a concise summary of the key contributions of each chapter (paper), aligned with the corresponding research question (RQ), within the main context of the entire PhD project.

Chapter 3 (Paper 1) aims to address RQ1 by examining the impact of the stringency of COVID-19 management policies on public emotions and how these emotions subsequently influence the effectiveness of policy implementation. Overall, this chapter has made a significant contribution to the field of public management by underscoring the managerial value of emotional cues embedded in social media messages, and offered a more efficient mechanism for promptly alerting policymakers to critical situations in public events.

Chapter 4 (Paper 2) addresses RQ2 by exploring the potential features that contribute to the spread of misinformation regarding government policies for managing COVID-19. In general, this chapter highlights the dynamics of information propagation characteristics in interpreting public opinions related to misinformed messages about government policies. It offers suggestions for improving the effectiveness of government-citizen interaction and fostering enhancements in public trust by emphasizing the importance of establishing two-way communication channels.

Chapter 5 (Paper 3) is dedicated to answering RQ3, which examines how risk perceptions influence the relationship between misinformation and the performance of COVID-19 management policies. This paper provides a comprehensive and all-encompassing interpretation of the risks associated with public emotional reactions and misinformation diffusion. By bridging the gap between theoretical constructs and real-world applications, this paper fosters the development of a more holistic and proactive approach in society, ultimately contributing to improved understanding and management of these complex phenomena.

2.2 Data and Methods Details

This section comprises four subsections: Data Description, Data Collection, Cleaning, and Preprocessing; Exploratory Data Analysis (EDA); and Data Analysis and Methods. Figure 2.1 provides an overview of the logical flow of the process.

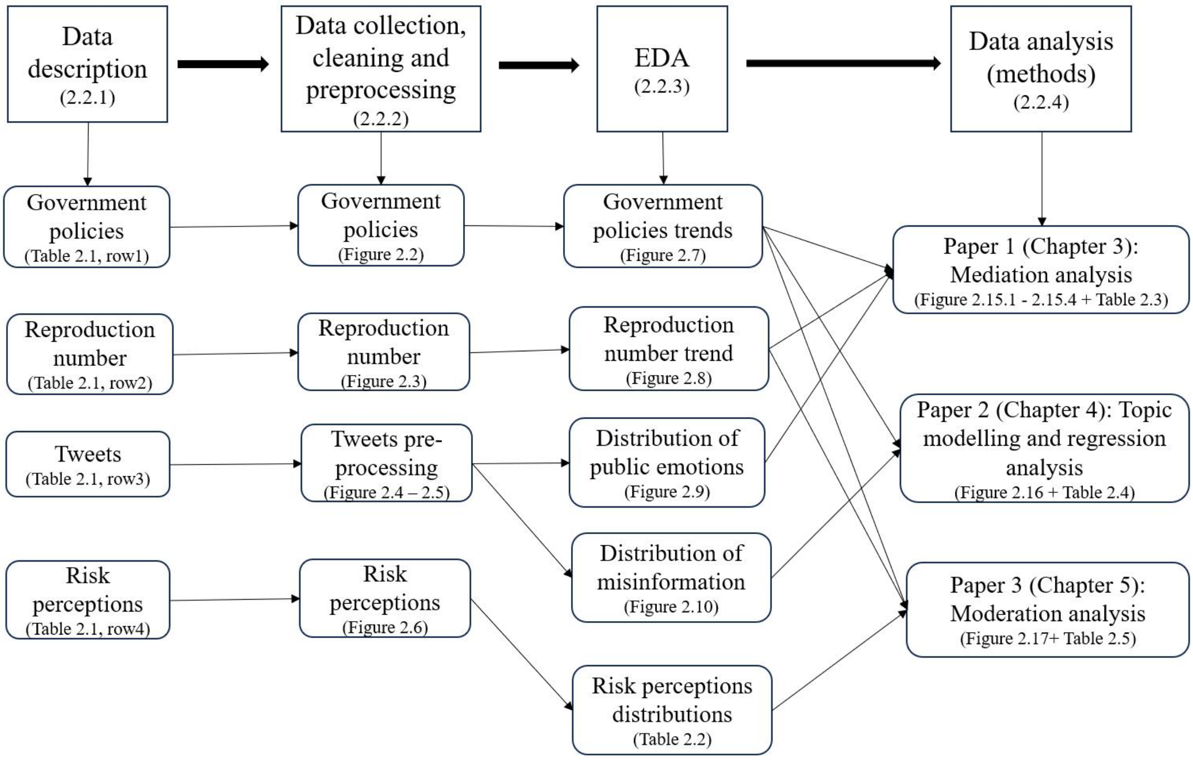


Figure 2.1 Logic Flow Chart of the Thesis

2.2.1 Data Description

All primary datasets utilized in the thesis are provided, along with pertinent information regarding the data source, size, time frame, and key attributes, as presented in Table 2.1. Additionally, comprehensive descriptions of the datasets are outlined in the main contents of the table.

Table 2.1 Detailed Dataset Description

Matadata	Chapters	Source	Size	Time Frame	Key Attributes	Main Contents

Government Policies	3, 4, 5	https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker	132M	2020-01 to 2022-02	Containment policies, economic policies, health policies, vaccination policies, country, dates.	This dateset covers policy information collected on which pandemic response measures in real-time were enacted by governments, and when.
Reproduction Number	3, 5	https://www.gov.uk/government/publications/reproduction-number-r-and-growth-rate-methodology	758	2020-01 to 2022-02	Infected cases, death cases, dates.	This dateset covers case numbers, which are used for predicting reproduction number.
Twitter Posts	3, 4, 5	https://www.x.com/	1.2M	2020-01 to 2022-02	Tweets, dates, geolocations, shares, comments, replies.	This dateset covers twitter posts discussing about government pandemic management policies.
Risk Perceptions	5	https://www.policyuncertainty.com/	8.1K	2000-01 to 2022-02	Economic uncertainty, geopolitical risk, climate risk, world uncertainty, dates, countries.	This dateset covers different risk and uncertainty index describing economy, geopolitics, climate, and overall world stability.

2.2.2 Data Collection, cleaning and preprocessing

This section encompasses a detailed description of the data collection process, along with the methodologies employed for cleaning and preprocessing each dataset. Furthermore, a diagram is provided for each dataset, illustrating the respective data processing pipeline.

2.2.2.1 Government Policies

Four types of government policies—containment, economic, health, and vaccination—were collected from the Oxford Covid-19 Government Response Tracker (OxCGRT) (Hale et al., 2020). This dataset records indicators on a scale to reflect the extent of government policies and aggregates them into a comprehensive suite of policy indices. Specifically, containment policy includes eight indicators to measure its strictness, economic policy has four indicators, health policy comprises eight indicators, and vaccination policy has three indicators. These indicators were normalized to convert them into four government policy indices. Additionally, other attributes such as countries and dates were included during data collection. Finally, the government policy dataset was restricted to the time range from February 1, 2020, to January 31, 2022, and limited to the UK. To provide more clarity on the processing details, Figure 2.2 illustrates the data processing pipeline for the government policy dataset.

date	C1	C2	C3	C4	C5	C6	C7	C8	E1	E2	E3	E4	H1	H2	H3	H4	H5	H6	H7	H8	V1	V2	V3
2020-02-01	1																						
2020-02-02	3																						
......																							
2022-01-31	2																						

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

(Equation 3.1)

date	Containment Policy	Economic Policy	Health Policy	Vaccination Policy
2020-02-01	33.3	0	43	33.3
2020-01-02	33.3	0	43	33.3
2020-01-03	33.3	0	43	33.3
2020-01-04	33.3	0	30	33.3
2020-01-05	33.3	0	30	60.6
2020-01-06	33.3	0	30	60.6
2020-01-07	66.6	34	30	60.6
2020-01-08	66.6	34	30	60.6
2020-01-09	66.6	34	30	60.6
2020-01-10	66.6	34	30	60.6
2020-01-11	66.6	34	66.6	60.6
2020-01-12	78	34	66.6	60.6
2020-01-13	78	60	66.6	80
2020-01-14	78	60	66.6	80
2020-01-15	78	60	66.6	80
2020-01-16	78	88	100	80
2020-01-17	100	88	100	80
2020-01-18	100	88	100	100
2020-01-19	100	88	100	100
......	......	......	......	......
2022-01-31	78	34	66.6	60.6

Figure 2.2 Data Processing Flow of Government Policies

2.2.2.2 Reproduction Number

The reproduction number dataset was collected from the relevant section of the UK Government's official website (GOV.UK, 2022), which records new daily case numbers. Based on these daily case numbers, the reproduction number was estimated using the Python Epyestim model (Cori et al., 2013), and it indicates the average number of secondary infections generated by a single infected individual over their infectious period. The dataset is restricted to the time range from February 1, 2020, to January 31, 2022. Figure 2.3 outlines the data processing pipeline for the reproduction number dataset.

date	new cases
2020-02-01	67864
2020-02-02	83819
2020-02-03	88899
2020-02-04	67706
2020-02-05	75467
2020-02-06	69549
2020-02-07	81824
2020-02-08	64407
2020-02-09	95092
2020-02-10	92308
2020-02-11	78959
2020-02-12	74087
2020-02-13	61060
2020-02-14	74437
2020-02-15	73624
2020-02-16	92762
2020-02-17	88467
2020-02-18	84742
2020-02-19	65461
……	……
2022-01-31	72994

Epyestim model
(Equation 3.2)

date	R(t)
2020-02-01	3
2020-02-02	4
2020-02-03	2
2020-02-04	4
2020-02-05	3
2020-02-06	1
2020-02-07	3
2020-02-08	4
2020-02-09	5
2020-02-10	2
2020-02-11	5
2020-02-12	5
2020-02-13	4
2020-02-14	5
2020-02-15	1
2020-02-16	3
2020-02-17	1
2020-02-18	5
2020-02-19	3
……	……
2022-01-31	1

Figure 2.3 Data Processing Flow of Reproduction Number

2.2.2.3 Twitter Posts

The Twitter posts, covering the same time frame from February 1, 2020, to January 31, 2022, were collected using the Twitter Application Programming Interface (API). The posts were gathered based on keywords that described the pandemic management policies implemented by the government. These keywords encompassed various dimensions to represent four types of government policies aimed at managing the COVID-19 pandemic: containment policy, economic policy, health policy, and vaccination policy.

Specifically, the containment policy has been articulated using keywords such as "school closure," "work from home," "cancel event," "gathering ban," "transport ban," "stay at home," "internal travel ban," and "international travel ban." Economic policy discussions typically involve keywords like "income support," "debt relief," "economic stimulus," and "international support." Health policy attracts attention when keywords such as "health campaign," "PCR testing," "contact tracing," "health investment," "vaccine investment," "face mask," and "protect elderly" are mentioned. Vaccination policy discussions revolve around keywords including "vaccine priority," "vaccine availability," and "vaccine investment." Therefore, when these keywords appear in online discussions, individuals are more likely to express their opinions or feelings in response to government management policies towards the virus. Additionally, the keyword "COVID-19" was included in the search list for each policy category. Collectively, keyword matching would extract tweets that convey meanings aligned with the objectives of the thesis.

Figure 2.4 provides further details on the process of cleaning and processing tweets. During this stage, when matching location names, if cities could correspond to multiple countries, this study assigned the country with the largest population center. This assumption was based on the notion that individuals from the largest city might be more likely to omit country identifiers, as illustrated in (Chum et al., 2021). While this method significantly enhances data availability, it may lead to location mismatches, potentially introducing errors in data analysis.

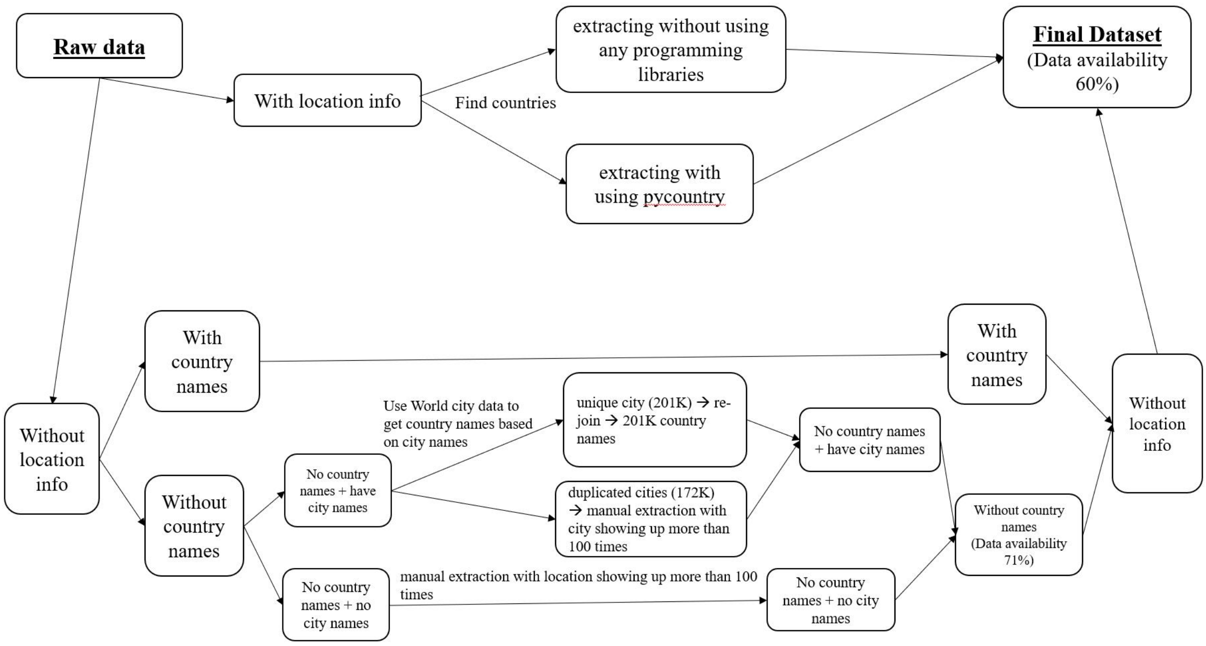


Figure 2.4 Data Processing Flow of Twitter Posts

After obtaining a cleaned version of the Tweets dataset, public emotions were predicted using the model proposed by Colnerič and Demšar (2018). In general, this model aims to convert textual data into numerical representations for the purpose of detecting emotions. In particular, the model is trained on a dataset of approximately 17 TB of space in uncompressed form and the training task took up to 8 days in a single GPU, covering 73 billion tweets collected for 7 years, which is widely recognised as one of the largest training data for emotion prediction purposes (Colnerič & Demšar, 2018). With such extensive temporal scope and sizeable magnitude of the training set, the model offered a universal emotion detection results, and its performance is less influenced by temporal variations, confirming the model's robustness and reliability. Moreover, this model was also built within two modes: multiclass and multilabel. Multiclass is built upon a single non-binary classifier for predicting the first emotional category, disregarding any other emotional keywords present later in the tweet. Classifiers in this setting only have to pick the most probable emotion from a set of all possible emotions. Multilabel mode is operated with multiple binary classifiers, meaning one per emotional category. For each of them independently, the classifiers have to provide a decision whether the tweet expresses that emotion or not.

In the end, the multilabel mode was chosen for emotion prediction due to its superior training performance and its alignment with real user preferences. This mode provides a series of probabilities for each emotion class. These emotion probabilities are continuous variables and range from 0 to 1, with 0 being the least probable that tweet comment intends to express a certain emotion and 1 being the maximum possibility of expressing that emotion. Then, the data was feed into deep learning models including baseline model (Bag-of-Words (BoW)), convolutional neural network (CNN), and recurrent neural network (RNN). Consequently, multilabel RNN classification model setting was selected, demonstrating superior performance compared to other model settings in relevant academic studies, achieving the highest F1-score of 70.0%. This suggests that the model is proficient in accurately comprehending the emotional meaning of tweets, making it a reliable tool for detecting emotions in social media messages. Figure 2.5 provides a flow of emotion prediction model.

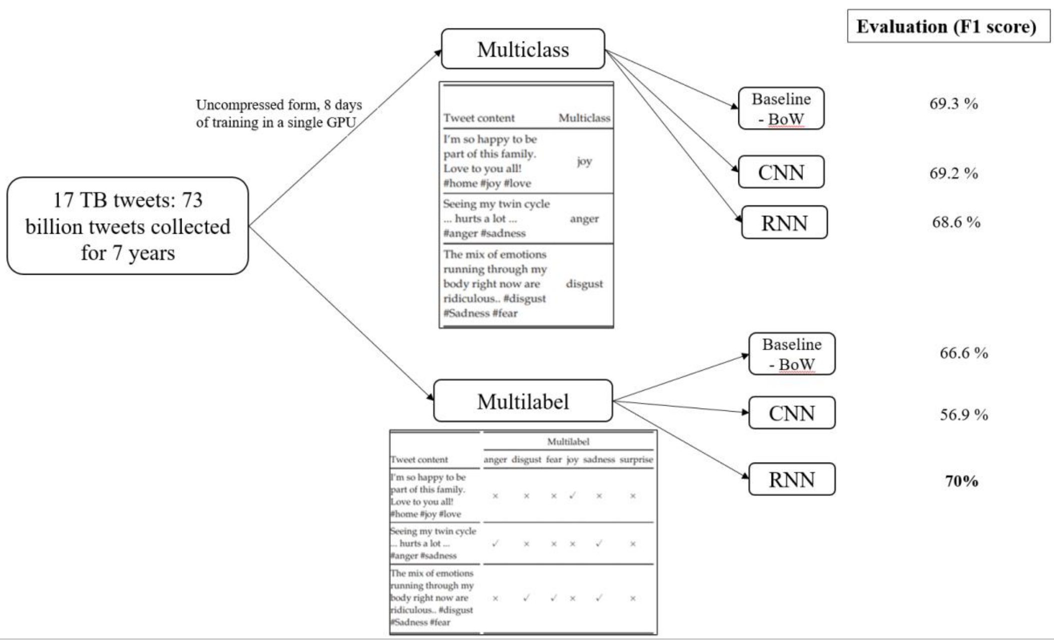


Figure 2.5 The Flow Chart of Emotion Prediction Model

2.2.2.4 Risk Perceptions

The risk perception dataset was sourced from the work of Baker et al. (2016), who developed a set of indices serving as proxies for risks and uncertainties arising from global regulatory frameworks. From the various attributes generated by this work, the following quantified risks were collected: economic policy uncertainty, geopolitical risk, climate policy uncertainty, and the world uncertainty index, along with country and date information. Additionally, the dataset was restricted to the time period from February 1, 2020, to January 31, 2022, and focused specifically on the UK. Figure 2.6 illustrates the data processing pipeline for the risk perceptions dataset.

country	date	Economic Policy Uncertainty	Geopolitical risk	Climate Policy Uncertainty	World Uncertainty Index
UK	2000-01-01	276	68	301	260
UK	2000-01-02	144	340	239	450
UK	2000-01-03	333	228	442	91
UK	....	315	260	304	479
US	2000-01-01	245	233	249	296
US	2000-01-02	388	219	200	181
US	2000-01-03	352	291	140	224
US	....	428	151	224	173
Canada	2000-01-01	269	234	293	117
Canada	2000-01-02	410	351	137	369
Canada	2000-01-03	413	427	126	427
Canada	....	416	182	236	112
China	2000-01-01	411	141	250	76
China	2000-01-02	125	440	412	437
China	2000-01-03	375	159	493	128
China	....	160	386	266	155

Step 1. Filter by country

Step 2. Focus on the time period starting from Feb 2020 and ending in Jan 2022

Step 3. Specifically select attributes related to risks and uncertainties (EPU, GPR, CPU, WUI)

country	date	Economic Policy Uncertainty	Geopolitical risk	Climate Policy Uncertainty	World Uncertainty Index
UK	2020-02-01	436	61	172	283
UK	2020-02-02	291	72	292	478
UK	2020-02-03	287	98	189	345
UK	....	99	121	149	473
UK	2022-01-31	437	297	229	364

Figure 2.6 Data Processing Flow of Risk Perceptions

2.2.3 Exploratory Data Analysis (EDA)

An essential EDA was conducted to identify patterns and trends in key datasets using visualization techniques. Specifically, it includes Figure 2.7 Government Policy Trends in the UK, Figure 2.8 Reproduction Number in the UK, Figure 2.9 Distribution of Emotions in the UK, Figure 2.10 The Distribution of Misinformation, and a table of monthly trends of various risk perceptions, as shown in Table 2.2.

2.2.3.1 Government Policies

Figure 2.7 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.

Figure 2.7 Government Policy Trends in the UK

2.2.3.2 Reprocution Number

The estimated reproduction number for each day is presented in Figure 2.8, 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.

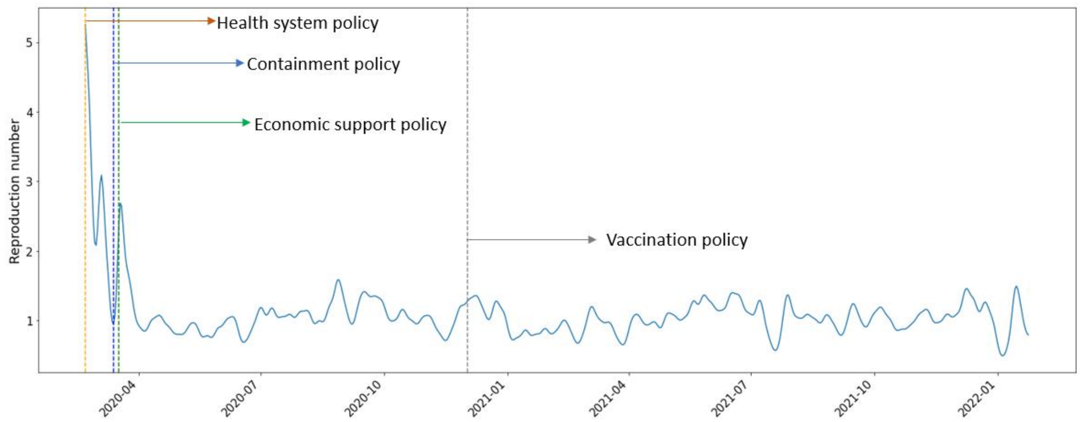


Figure 2.8 Reproduction Number in the UK

2.2.3.3 Twitter Posts

Twitter posts serve two purposes: generating public emotions and predicting misinformation. The distributions of these two datasets are presented in Figure 2.9 and Figure 2.10, respectively.

Figure 2.9 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.

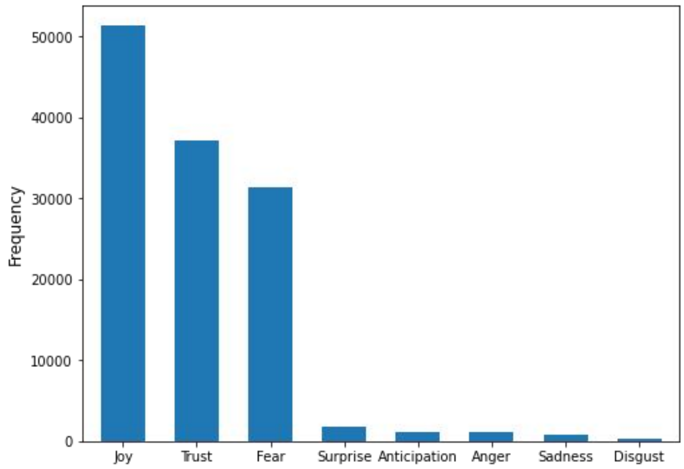


Figure 2.9 Distribution of Emotions in the UK

As illustrated in Figure 2.10, the outcomes from the pre-trained misinformation classification model revealed that misinformation outweighed non-misinformation throughout the sample period. This finding is consistent with previous research that indicates that misinformation has a wider reach than the truth (Garimella & Eckles, 2020; Vosoughi, Roy, & Aral, 2018).

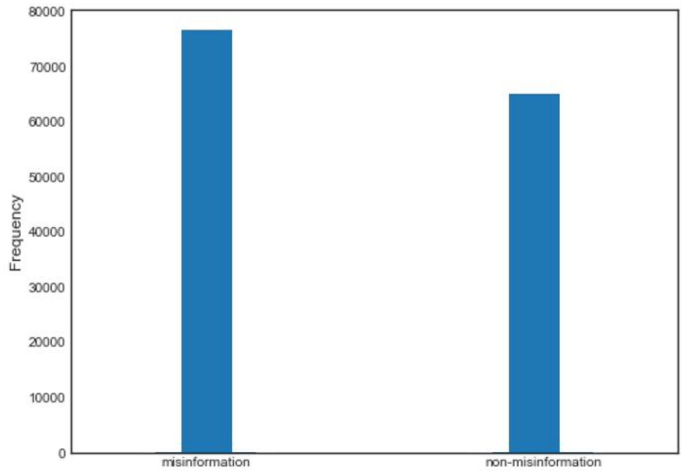


Figure 2.10 The Distribution of Misinformation

2.2.3.4 Risk Perceptions

The following table displays the evolving trends of different risk perceptions, as illustrated in the left column. Specifically, economic policy uncertainty peaked at the onset of the COVID-19 pandemic and subsequently declined, as depicted in Figure 2.11. Conversely, geopolitical risks continued to increase throughout the entire pandemic period, as shown in Figure 2.12. In Figure 2.13, climate policy uncertainty exhibited a fluctuating trend but overall displayed an upward trend. Lastly, the World Uncertainty Index generally declined as the pandemic was managed and controlled over time, as indicated in Figure 2.14.

Table 2.2 Risk Perceptions Trends

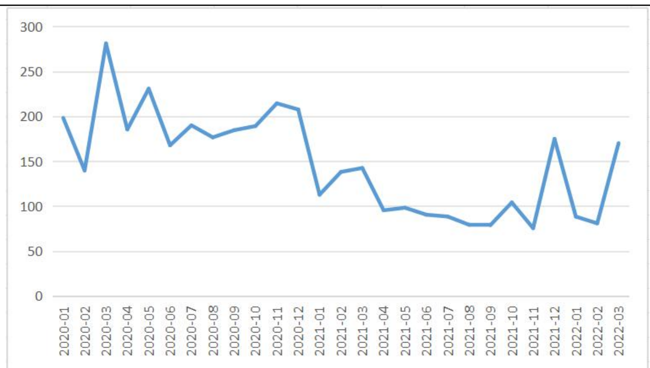
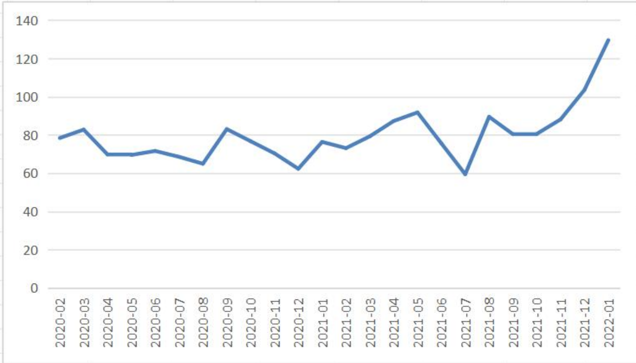
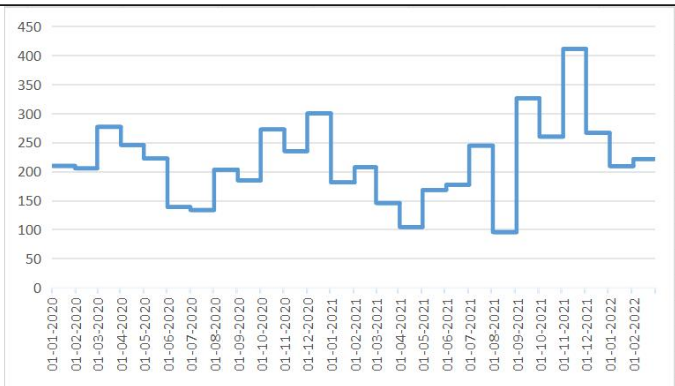
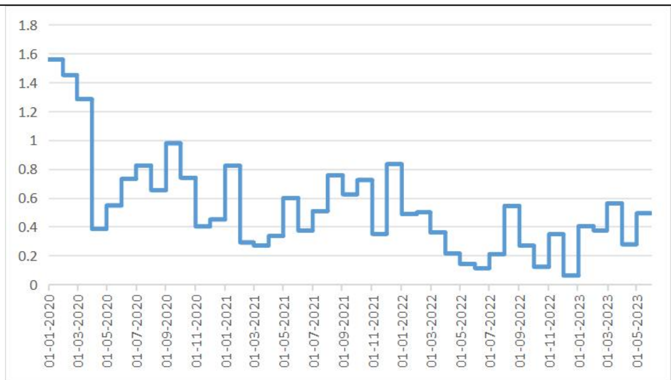
Risk Perception Types	Risk Perception Trends (monthly)
Economic Policy Uncertainty (EPU)	

	Figure 2.11 monthly EPU
Geopolitical Risk (GPR)	 Figure 2.12 monthly GPR
Climate Policy Uncertainty (CPU)	 Figure 2.13 monthly CPU
World Uncertainty Index (WUI)	 Figure 2.14 monthly WUI

2.2.4 Data Analysis and Methods

This section clarifies the relationship among the multiple datasets utilized in each chapter and elucidates the processes employed for aligning, integrating, and validating these datasets to ensure consistency and reliability. Additionally, it discusses approaches and methodologies for resolving conflicts or discrepancies that arose during the integration of these datasets.

2.2.4.1 Chapter 3 (Paper 1)

In Chapter 3 (Paper 1) of the thesis, the objective is to address RQ1 by examining how the stringency of COVID-19 management policies affects public emotions, subsequently influencing the effectiveness of policy implementation during the pandemic. To explore the relationship between government policies and the reproduction number through the mediation mechanism of public emotions, three datasets are combined: government policy, public emotions (encompassing anger, joy, sadness, trust, surprise, disgust, fear, and anticipation), and the reproduction number, as illustrated in Figure 2.1. Mediation analysis methods are applied in this chapter to examine these relationships.

Based on the mediation analysis structure, the relationships among these data can be described as follows: government policy is intended to manage and control the reproduction number, serving as the independent variable (IV) in the model. Public emotions, which are influenced by policies and in turn influence the reproduction number, function as mediators in the model. The reproduction number serves as dependent variable (DV) in the model. Given the existence of four different types of policies, four corresponding mediation models are developed, as depicted in Figures 2.15.1 to 2.15.4. By adhering to the steps of mediation analysis (Zhao, Lynch Jr, and Chen 2010), the relationships between the IV and mediators, mediators and DV, and the mediation effect of the IV on the DV were tested.

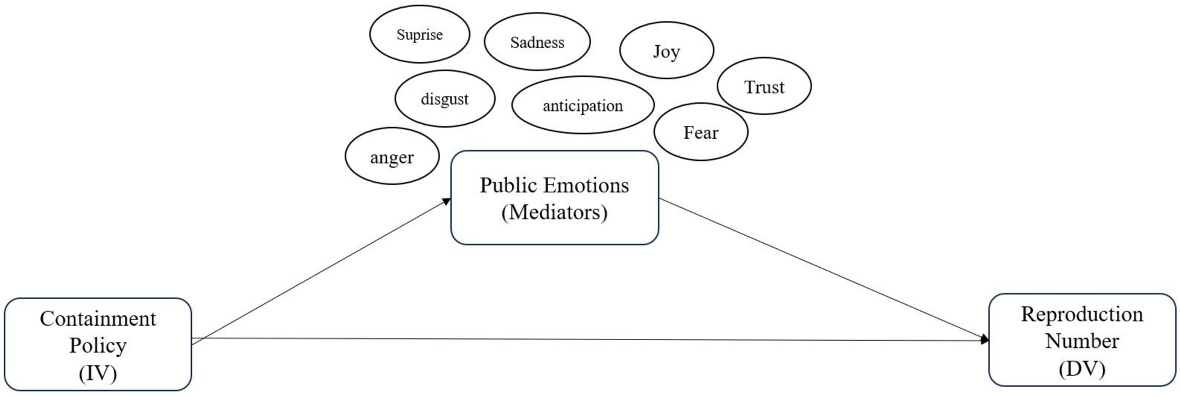


Figure 2.15.1 Mediation Model Strucuture (containment policy, Chapter 3)

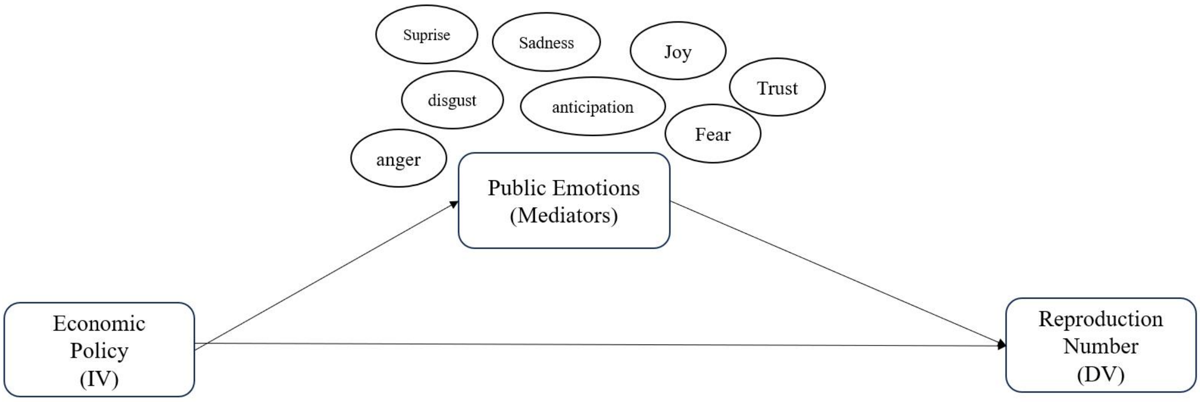


Figure 2.15.2 Mediation Model Strucuture (economic policy, Chapter 3)

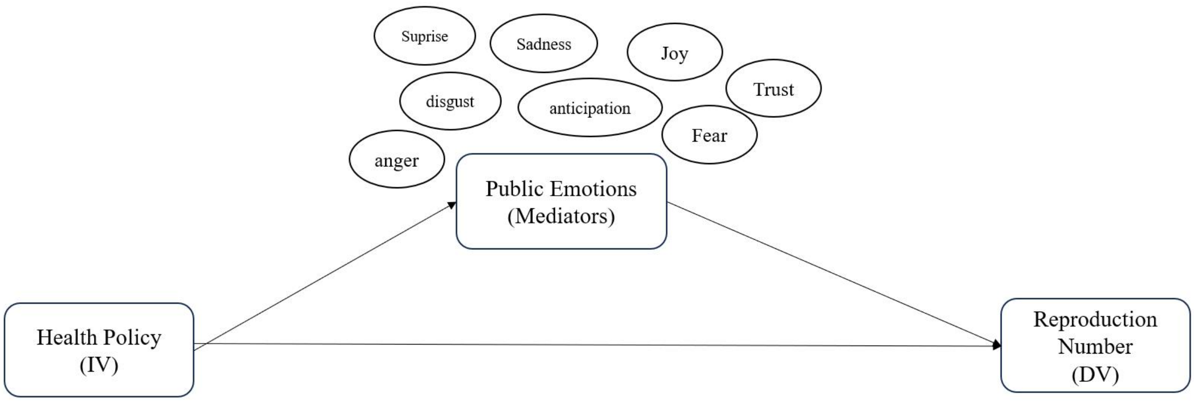


Figure 2.15.3 Mediation Model Strucuture (health policy, Chapter 3)

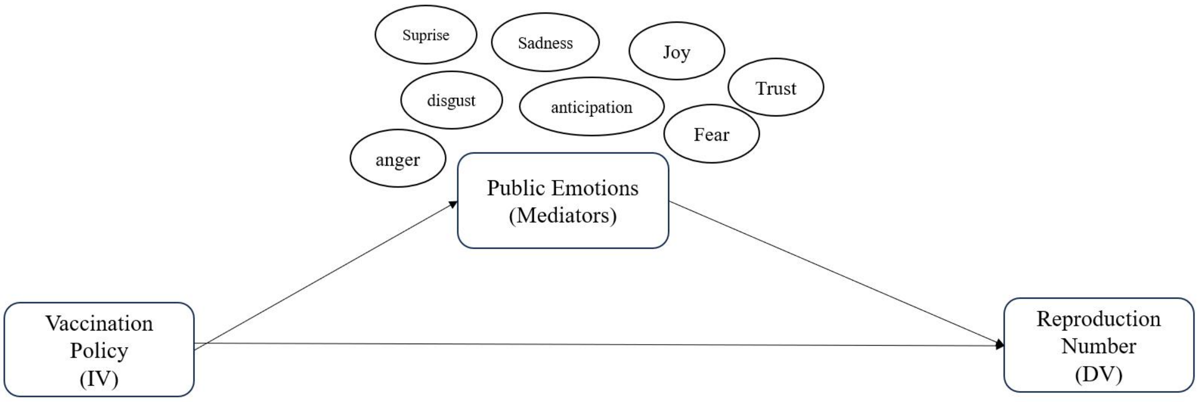


Figure 2.15.4 Mediation Model Strucuture (vaccination policy, Chapter 3)

During the integration process, since the data had already been reorganized on a daily level, the three datasets were aligned based on the date. In cases where there were discrepancies in the length of the date ranges, the data was kept within the same time frame, specifically from February 2020 to January 2022, focusing on the UK. To assess the consistency and reliability of the government policies, which are presented as scale data, a reliability test was conducted. Cronbach's alpha was calculated as it is a widely used indicator of scale reliability, ranging from 0 to 1. A value closer to 1 indicates higher reliability, with 0.6 serving as the threshold for judging reliability. As shown in Table 2.3, the ordinal variables representing the government policies demonstrate reliability.

Table 2.3 The Reliability Check for Government Policy Dataset

Policy types	Reliability coefficient of its components
Containment policy	0.9
Economic policy	0.6
Health policy	0.6
Vaccination policy	0.8

2.2.4.2 Chapter 4 (Paper 2)

In Chapter 4 (Paper 2), the focus is on addressing RQ2 by exploring the significant factors that contribute to the dissemination of misinformation regarding government policies during the COVID-19 pandemic. As depicted in Figure 2.1, the primary datasets used in this investigation are government policies and misinformation, which are aligned based on the time frame and location. The aim is to investigate the dynamics shaping misinformation based on information factors and to explore the potential influence of government policies on COVID-19-related misinformation. To achieve this, topic modeling and regression modeling are employed in this Chpater.

Topic modeling is a valuable method for uncovering essential information factors within misinformed messages, including user engagement, message framing, content similarities, and content topics. These attributes are integrated together based on the Elaboration Likelihood Model (ELM). During the integration process, since the data had already been reorganized on a daily level, the three datasets were aligned based on the date. In cases where there were discrepancies in the length of the date ranges, the data was kept within the same time frame, specifically from February 2020 to January 2022, focusing on the UK. This allowed for a comprehensive analysis of the factors contributing to the dissemination of misinformation regarding government policies during the COVID-19 pandemic.

To further test the hypotheses, a regression model, as depicted in Figures 2.16, was used where user engagement, message framing, content similarities, and content topics were treated as independent variables (IVs), and misinformation as dependent variable (DV). In addition, to ensure the reliability of the measurements, a range of methods were employed to validate the datasets, as detailed in Table 2.4. These methods were designed to ensure the accuracy and consistency of the data, thereby enhancing the trustworthiness of the analysis.

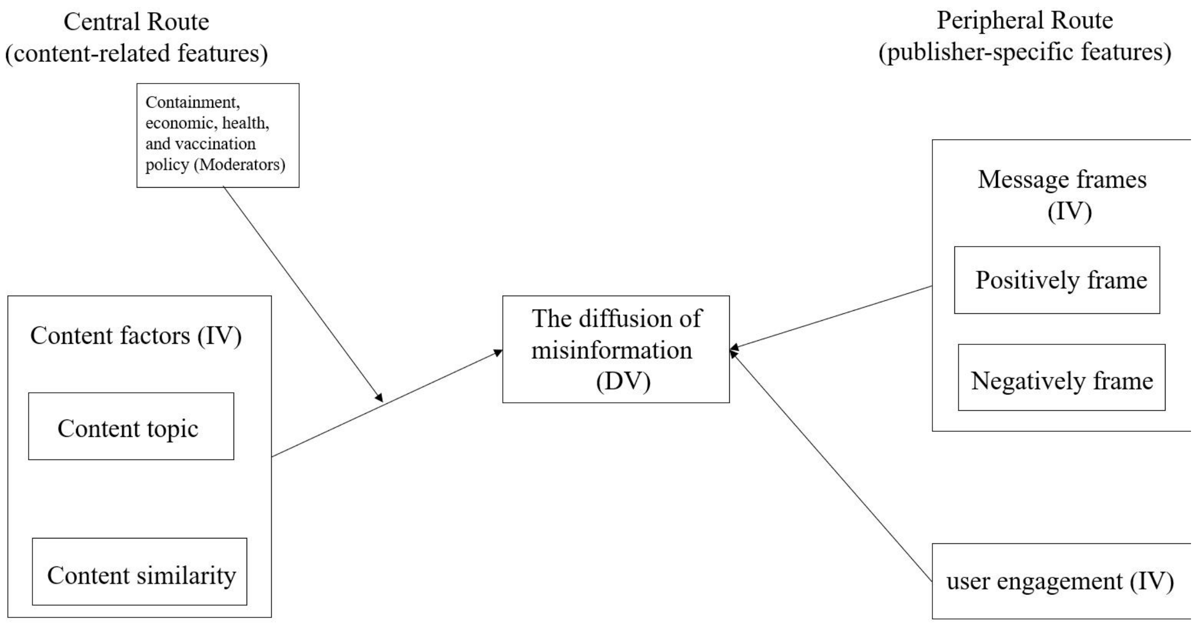


Figure 2.16 Regression Model Strucuture (Chapter 4)

Table 2.4 Methods to Secure Data Reliability

Data	Machine learning models	Source of reliable measurement methods
User engagement	An extensively applied engagement metric (details in Table 4.3)	Bonsón, Royo, and Ratkai (2015)
Message framing	Python TextBlob package	The emotions-as-frames approach in Nabi et al (2020)'s work
Content similrity	Term Frequency - Inverse Document Frequency	(Feng, Hui, Deng, & Jiang, 2021)
Content topics	Latent Dirichlet Allocation (Topic Modelling)	(Blei et al., 2003)
Misinformation	Logistic regression, Naive Bayes, Support Vector Machine	(Patwa et al., 2021)

2.2.4.1 Chapter 5 (Paper 3)

In Chapter 5 (Paper 3), the focus is on answering RQ3, which investigates how perceptions of risk affect the relationship between misinformation and the performance of COVID-19 management policies during the pandemic. To achieve this, three primary datasets - misinformation, risk perception, and reproduction number - were aligned together based on the time frame and location, as illustrated in Figure 2.1. The aim was to uncover the impact of misinformation on policy implementation and to examine how embedded risks and uncertainties within policy information moderate its influence. To analyze this relationship, a moderation analysis method was utilized in this Chapter.

More specifically, these datasets were integrated together based on the Protection Motivation Theory (PMT). In this integration, since the data had already been reorganized on a daily basis, the three datasets were aligned based on the date. In cases where there were discrepancies in the length of the date range, they were kept within the same time frame, specifically from February 2020 to January 2022, and focused on the UK. To test the hypotheses using moderation analysis model, misinformation served as the independent variable (IV), risk perceptions were the moderators, and the reproduction number was the dependent variable (DV), as illustrated in Figure 2.17.

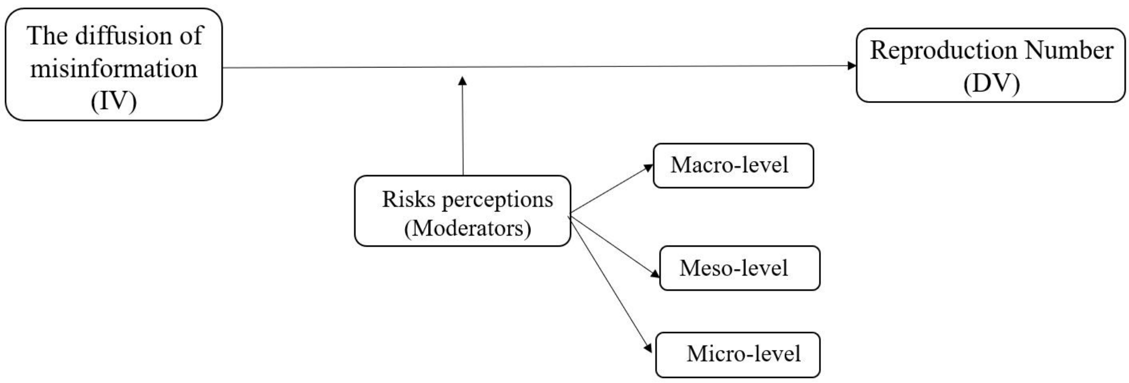


Figure 2.17 Moderation Model Strucuture (Chapter 5)

Meanwhile, three different types of risk perceptions were extracted from newspapers and measured relied on an extensive automated text-search of news media coverage, which incorporated human readings of 12,000 newspaper articles. This approach enhanced the reliability and generalizability of the measurement, as detailed in Table 2.4 (Baker et al., 2016).

Table 2.5 Text Mining Sources for Risk Perception Data

Data	Text mining sources
Economic Policy Uncertainty	Eleven UK newspapers: The FT, The Times and Sunday Times, The Telegraph, The Daily Mail, The Daily Express, The Guardian, The Mirror, The Northern Echo, The Evening Standard, and The Sun.
Geopolitical Risk	Eight leading US newspapers: Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today and the Wall Street Journal.
Climate Policy Uncertainty	Ten leading US and UK newspapers related to adverse geopolitical events: Chicago Tribune, the Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, the Los Angeles Times, The New York Times, USA Today, The Wall Street Journal.
World Uncertainty Index	The Economist Intelligence Unit (EIU) country reports offer a comprehensive examination of various factors and their impact on the global landscape.

Chapter 3. Mediation Analysis of Public Emotions in response to Policy Implementation Performance during Crises: The Case of COVID-19 Management Policies in the UK

3.1 Abstract

Understanding public emotions in crises is crucial to effective public policy management for governments. This study examines the relationship between pandemic management policies, the performance of management policies, and fundamental emotions according to Plutchik's Wheel of Emotion, in the context of COVID-19 in the UK. The findings validate the role 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. The study contributes to the public management literature by emphasizing the importance of the heterogeneity of emotions.

Keywords: COVID-19, government policy, public emotions, pandemic management performance, mediation analysis

3.2 Introduction

Effective governmental policy orchestration is widely acknowledged as pivotal in enhancing management capacity during crises, as exemplified by the COVID-19 pandemic (Zheng, Li & 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 (Ku, Kim & Oh, 2022).

Due to policy interventions that drastically restricted people's daily lives (Haug et al., 2020), public emotions, following the initially predominant social environmental messages addressing crisis-related human responses, became the next most prevalent information circulating on social media (Reuter & 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 government policies, diverse public emotions are unequivocally recognised as pivotal factors influencing the outcomes of management policies (Chou & Budenz, 2020; Heffner, Vives, & FeldmanHall, 2021; Jungmann & 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 & 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), the study endeavours to illuminate the manner in which individuals' emotions are shaped by public policies, subsequently impacting the management policy performance of specific societal occurrences (Marcus, Neuman & 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 utilising 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, the theoretical innovation lies in the commitment to a more nuanced examination of the AIT, empowering us to intricately dissect the relationships between government policies, public emotions, and management performance, thereby enriching the interpretation of the theory.

To address this matter, this study 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, the 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, the results supports and enriches AIT by demonstrating that public emotions, stemming from diverse government policies, influence policy performance through mediating mechanisms (Marcus, Neuman & MacKuen, 2000). Moreover, this study has confirmed earlier research that diverse policy settings impact emotions of the same polarity distinctively (Liu, Shahab & Hoque, 2022). Further, the study contributes to optimising policy evaluation in public policy management models by articulating scenarios where public emotions potentially impact pandemic management performance (Jones & Chase, 1979). Regarding policy implications, this study suggests to closely monitor fluctuations in public emotions to enhance public health rapid response capacity of public health system (Zheng, Li & 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 this study has 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 prioritise addressing the needs of populations experiencing elevated emotional stress to mitigate widespread virus transmission.

3.3 Literature and Hypotheses

3.3.1 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 & Béland, 2013). These domains encompass areas such as political issue management (Vasilopoulos, 2019), public health (Renström & Bäck, 2021), public communication (Lee & 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, Neuman & MacKuen, 2000). this study employed AIT as the theoretical lens, 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 (Marcus, Neuman & MacKuen, 2000; Finucane et al., 2000). Public emotions triggered by government management policies can have varied implications for their effectiveness, either positively or negatively. Recognising 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, Neuman & 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 sensitise individuals to perceived risks and mobilise them to make decisions based on their current emotional states during the policy implementation (Marcus, Neuman & 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 emphasised the dynamics of information processing and the significance of emotions in this regard (Marcus, MacKuen, & Neuman, 2011; Marcus, Neuman & 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 (Xie et al., 2011; Gaspar et al., 2016; Lee & Choi, 2018). 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.

3.3.2 Hypotheses

3.3.2.1 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., 2020). 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 & Hoque, 2022; Vemprala 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 (Wu, Xiao & 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 & Luli, 2021).

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

H1. Governments' COVID-19 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.

3.3.2.2 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 (Zhou et al., 2020; Li et al., 2023). 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, Ku & Le Nguyen, 2022; Feng et al., 2021). Building upon these established findings, this study posits 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 toward an event (Han & Baird, 2022; Yu, Eisenman & 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 behavioral responses within specific contextual circumstances. Specifically, certain emotions—notably positive ones—guide individuals towards perceiving situations favourably, fostering behaviour aligned with government policies emphasising compliance. Conversely, negative emotions may promote non-compliance with public health policies, resulting in suboptimal policy performance (Ormond, Warkentin & Crossler, 2019; D'Arcy & The, 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 & 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 (Turner, 2022; Ormond, Warkentin & Crossler, 2019). 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 toward an event, a more explicit examination of how emotions can contribute differently to government pandemic management performance has been overlooked. Therefore, this study proposes that:

H2. Public emotions have significant effects on pandemic management performance during the COVID-19 period.

3.3.2.3 The Mediating Role of Public Emotions

Policies implemented by governments can prompt superior performance in managing the pandemic (Zheng, Li & 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 & 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 incentivise individuals to access to required hygiene equipment and adopt protective behaviours, thus mitigating the virus transmission (Li & 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 endeavor, 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 (Renström & Bäck, 2021; Han et al., 2022), 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, 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, Li & 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 & 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), this study expects that heterogeneous indirect effects of emotions exist between governments' pandemic policies and their subsequent performance. Figure 2.1 presents the theoretical framework, and this study thus proposes that:

H3. Public emotions mediate the relationship between the COVID-19 pandemic management policies and their 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.

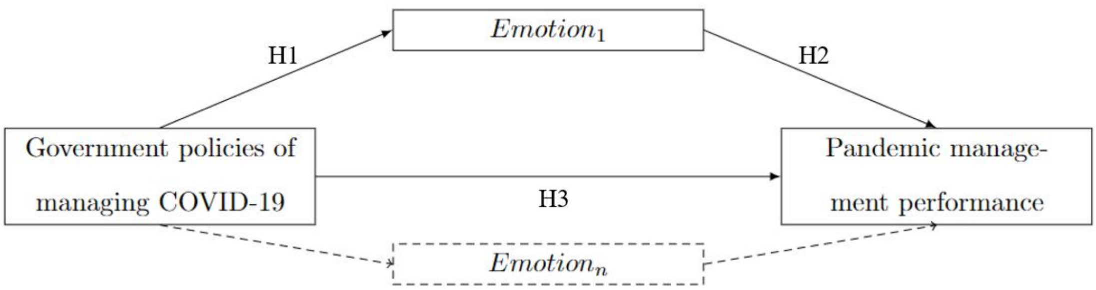


Figure 3.1 Main Theoretical Framework

3.4 Methodology

3.4.1 Data Collection and Preprocessing

The study has 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 3.2 shows distinct peaks during the Beta, Delta, and Omicron variant periods.

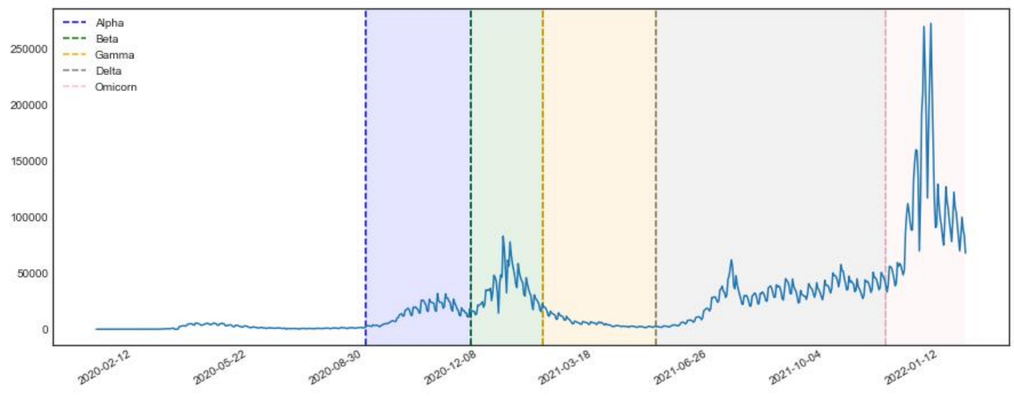


Figure 3.2 Cases in the UK

Second, government policies adopted by the UK government are sourced from the Oxford COVID-19 Government Response Tracker (OxCGRT) project (Hale et al., 2020). 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 a suite of policy indices. Over 400 volunteers from the University of Oxford and partner organisations 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 3.1 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. this study excludes some components (highlighted in Table 2.1 by $), as they do not express policy stringency scales.

Table 3.1 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

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. Utilising the Twitter API and the Python snscrape package (TwitterSnscrape, 2008), this study extracted 1.2 million related tweets based on OxCGRT keywords listed in Table 2.2. 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, this study assigned the country with the largest population center, 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 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, this study filtered for English-only tweets, removed HTML tags, @usernames, numbers, punctuation marks, special characters, stop words, and tokenised the text.

Table 3.2 OxCGRT Keywords and The Reliability Check for Policies

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

3.4.2 Measures

3.4.2.1 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., 2020) as

$$I_{j,t} = 100\frac{v_{j,t}-0.5(F_j- f_{j,t})}{N_j}, \tag{3.1}$$

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, this study 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 3.2), 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.

3.4.2.2 Dependent Variable

The pandemic management policy 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. this study employed the Python epyestim package to estimate the reproduction number as

$$R_t = \frac{E[I_t]}{\sum_{s=1}^{t} I_{t-s} w_s}, \tag{3.2}$$

where R_t is the reproduction number at calendar time *t*; $\mathrm{E}[I_t]$ 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).

3.4.2.3 Mediating Variables

Plutchik (1980)'s theory, serving as a foundational framework for conceptualising emotions in textual data, has emerged as the most useful classification scheme for emotive language analysis (Chung & 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 & 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 & 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, this study 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 emotion category.

3.4.2.4 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).

3.4.3 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 & Kenny, 1986; Hayes, 2009). As presented in Figure 3.3, 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

$$c = c^{'} + \sum_{n=1}^{\infty} a_n b_n, \tag{3.3}$$

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, this study tested 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.

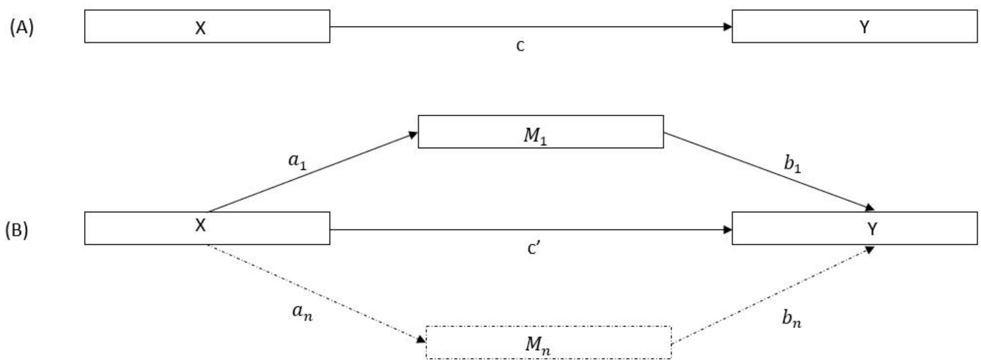


Figure 3.3 Mediation Analysis Model

3.5 Findings

The descriptive statistics and Pearson correlations are reported in Table 3.3. In Hypothesis 1, this study analyses the effects of four government policies on different emotions and observe varying outcomes. Model 1.1 in Table 3.4 (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 3.5 (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 3.6 (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 3.7 (vaccination policy) reflect that increasing policy stringency causes people to be angrier and less trustful.

3.5.1 Mediation Analyses

To test mediating effects, this study followed Zhao, Lynch Jr, and Chen (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 3.8 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, Lynch Jr, and Chen 2010).

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 3.9, are established. To test H3b, Model 2.3 in Table 3.5 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 3.10 indicates that the mediating effect is significant, as the bootstrapped confidence interval around the indirect effect does not include zero [95% CI(1.0 × 10^{-5} – 2.2 × 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 3.6 presents that *Fear* has a positive influence on the reproduction number. Additionally, the effect of health policy on the reproduction number becomes attenuated, changing from 0.0065 to 0.0063. Moreover, Model 3.3 in Table 3.10 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.

Table 3.3 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 3.4 Hypothesis Testing Model for Containment Policy

Variables	Model 1.1 (M)								Model 1.3 (Y)	
	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 3.5 Hypothesis Testing Model for Economic Policy

Variables	Model 1.1 (M)								Model 1.3 (Y)	
	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 3.6 Hypothesis Testing Model for Health Policy

Variables	Model 1.1 (M)								Model 1.3 (Y)	
	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	−0.048***	− 0.007*	-0.009	-0.001	-0.000
	(0.018)	(0.027)	(0.004)	(0.005)	(0.019)	(0.018)	(0.003)	(0.020)	(0.007)	(0.007)
Average policy strictness	0.002	0.006*	0.002***	− 0.002***	0.004	0.004	0.000	0.003	−0.004***	−0.004***
	(0.003)	(0.004)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.01)	(0.001)
Mobility trends for grocery and pharmacy	0.000	0.004	-0.001	0.000	-0.001	0.001	-0.000	0.001	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	-0.003 (0.003)	-0.004 (0.005)	0.000 (0.001)	0.000 (0.001)	0.000 (0.003)	0.003 (0.003)	-0.000 (0.001)	0.002 (0.004)	-0.002 (0.001)	-0.002 (0.001)
Mobility trends for residential areas	-0.006 (0.006)	-0.004 (0.010)	-0.003^{**} (0.002)	0.002 (0.002)	-0.002 (0.007)	0.007 (0.007)	0.000 (0.001)	0.011^{*} (0.007)	-0.010^{***} (0.002)	-0.010^{***} (0.002)
Independent variable										
Health policy	-0.146 (0.155)	-0.090 (0.234)	-0.075^{**} (0.037)	0.087^{**} (0.044)	-0.412^{**} (0.164)	-0.174 (0.161)	0.007 (0.029)	-0.242 (0.171)	-0.2547^{***} (0.058)	-0.2464^{*} (0.058)
Mediators										
Fear										0.110^{*} (0.074)
R^2	0.022	0.012	0.046	0.018	0.011	0.029	0.035	0.023	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 3.7 Hypothesis Testing Model for Vaccination Policy

Variables	Model 1.1 (M)								Model 1.3 (Y)	
	Anger	Disgust	Fear	Joy	Sadness	Surprise	Trust	Anticipation	Y-X	Y-X+M
Control variables										
Variant stage	-0.066^{*} (0.039)	-0.066 (0.060)	-0.007 (0.011)	0.007 (0.011)	-0.041 (0.042)	-0.016 (0.041)	0.006 (0.007)	-0.001 (0.002)	0.016 (0.017)	
Average policy strictness	-0.001 (0.002)	0.005 (0.003)	0.001 (0.001)	-0.001^{*} (0.001)	-0.001 (0.002)	0.002 (0.002)	0.000 (0.000)	0.004 (0.044)	-0.008^{**} (0.001)	
Mobility trends for grocery and pharmacy	0.001 (0.002)	0.005 (0.003)	-0.001 (0.001)	0.000 (0.001)	-0.001 (0.002)	0.001 (0.002)	-0.000 (0.000)	0.001 (0.003)	0.006^{***} (0.001)	
Mobility trends for public transport hubs	-0.004 (0.003)	-0.004 (0.005)	0.000 (0.001)	0.000 (0.001)	-0.001 (0.003)	0.004 (0.003)	-0.000 (0.001)	0.001 (0.003)	-0.004^{**} (0.001)	
Mobility trends for residential areas	-0.007 (0.006)	-0.005 (0.010)	-0.003^{**} (0.002)	0.002 (0.002)	-0.000 (0.007)	0.009 (0.007)	0.001 (0.001)	0.002 (0.004)	-0.011^{**} (0.003)	
Independent variable										
Vaccination policy	0.005^{***} (0.002)	0.003 (0.002)	0.000 (0.000)	0.000 (0.000)	0.002 (0.002)	-0.002 (0.002)	-0.001^{**} (0.000)	-0.001 (0.002)	-0.001^{*} (0.001)	
R^2	0.034	0.014	0.042	0.012	0.004	0.029	0.041	0.020	0.229	

Y, reproduction number; X, vaccination policy; M, emotions. Standard errors are reported in parentheses.

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

Table 3.8 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 3.9 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.

Table 3.10 Tests of Indirect Effects

Mediators	95% CI Economic policy (Model 2.3)		95% CI Health policy (Model 3.3)	
	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, confident interval

To better understand the importance of emotions' mediating effects, the proportion mediated is utilised 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 & Hayes, 2008; Zhao, Lynch Jr & Chen, 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 3.3 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, this study presents an illustrative example extracted from a randomly selected user from the 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 emphasises the central theme, namely, that individuals' emotional reactions to government policy announcements are a critical determinant in pandemic management.

3.5.2 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 (Massey Jr, 1951). K-S statistic in Table 3.11 shows that the reproduction number, emotions and policies are all significant ($p < 0.05$), implying a non-normal distribution. To resolve this, this study applied Hayes's bootstrap method (Ng & Lin, 2016). Second, an alternative model incorporating additional control variables in Table 3.12, 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 the study.

Table 3.11. 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 3.12. Robustness Check

	Coefficient	Standard Error	Lower CI	Upper CI
Mediation model 1				
X_e → Surprise	-0.0004^{**}	0.0002	0.0001	0.0007
Surprise → Y	0.281^{**}	0.136	0.057	0.506
Total effect	-0.0400^{***}	0.0006	0.0026	0.0046
Direct effect	-0.0350^{***}	0.0006	0.0025	0.0045
Indirect effect	-0.0005^{***}	0.0001	**0.0000**	**0.0002**
Mediation model 2				
X_h → Fear	-0.002^{**}	0.0009	-0.0034	-0.0006
Fear → Y	0.116^{*}	0.068	0.005	0.228
Total effect	-0.0102^{***}	0.0014	-0.0126	-0.0080
Direct effect	-0.0101	0.0014	-0.0124	-0.0078
Indirect effect	-0.0001	0.0001	**-0.0005**	**-0.0000**

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

3.6 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 & Hoque, 2022; Renström & 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, the 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, the 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 & Baird, 2022; Zheng, Li & Sun, 2021).

3.6.1 Theoretical Contributions

First, the 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 & 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 (Castanheira, Sguera & 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 (Castanheira, Sguera & Story, 2022). Hence, the 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 & Baird, 2022).

Second, the 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 (Liu, Shahab & Hoque, 2022; Gaspar et al., 2016). This explanation is supported by one of the 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 & 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 behaviors of accepting a novel vaccine; thus, the emotion that best characterises this scenario is anger, rather than fear, which also aligns with the findings. Overall, the 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, the study bears meaningful implications on public policy and public management literatures, as it contributes to the public policy management model by optimising 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 & Chase, 1979). As Bryson, George, and Seo (2022) observed, emotions would guide goal-directed efforts to be more effectively materialised 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 &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, the study reveals emotion's potential to aid in the optimisation 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 prioritizse 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 & Stéphan, 2021).

3.6.1 Policy Implications

the 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, Li & 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 analyzing 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 & 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, the 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 the 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 3.9) leads to an estimated 8% reduction in the reproduction number. Applying this framework to the UK context, this study anticipates 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, this study recommended 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 prioritise the mitigation of tensions stemming from threshold-crossing emotions. These actions, undertaken by policymakers who recognise 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, the findings provide empirical evidence supporting the streamlining of pandemic management policy design (Newman, Cherney & 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 & 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 & Head, 2017). Given this imperative, this study strongly recommends 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 prioritise 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, the 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.

3.6.3 Limitations and Future Research

This study has acknowledged several limitations. First, this study is 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 the 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, this study encourages 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.

Chapter 4. Uncovering the Factors Leading to Misinformation Regarding Government Policies During a Public Health Event: Insights from the UK Pandemic Intervention Measures

4.1 Abstract

Understanding the mechanisms underlying misinformation diffusion is crucial for policymakers, enabling them to devise effective strategies to mitigate its impact on information systems. Despite the extensive focus on cognitive and social-psychological perspectives in contemporary misinformation research, an investigatory viewpoint of information diffusion remains underexplored. Drawing on the Elaboration Likelihood Model, which considers both content and peripheral factors influencing information propagation, this study uncovered the dynamics shaping misinformation diffusion during crises, using the COVID-19 pandemic as an illustrative case. Hypotheses were formulated and tested on a dataset of 144K Twitter posts between February 2020 and January 2022 in the United Kingdom. The study revealed a negative association between user engagement, the frequency of specific content topics (face protection, international economic support, and screening methods), and misinformation diffusion. Additionally, government management policies exhibited varying moderating effects on misinformation diffusion, depending on their characteristics. These findings underscore the significance of fostering two-way communication between government and citizens in crisis policy implementation. Prioritizing the dissemination of information on protective behaviors and delivering fact-based messages is essential to instill public trust and counteract the spread of misinformation.

Keywords: misinformation; government intervention policies; crisis management; user engagement; topic modeling.

4.2 Introduction

With the rapid development of digital communication channels, the proliferation of misinformation has emerged as a significant and pressing concern (Moravec et al., 2022; Mostagir & Siderius, 2023). Misinformation is defined as inaccurate claims that act as an umbrella term for interchangeable expressions including conspiracy theories, false rumors, fake news, propaganda, and disinformation (Wu et al., 2019; Shirish et al., 2021). With its expeditious expansion in cyberspace, such as social media platforms, misinformation has intruded upon personal privacy, damaged organizational reputations, and triggered public panic (Moravec et al., 2022). This becomes even more critical during crisis since the dissemination of misinformation can intensify and complicate the crisis scenario, leading to hampered emergency response efforts, misallocation of vital resources, and ineffective governmental administration (Dwivedi et al., 2020). For example, misinformation about the severity of the COVID-19 pandemic and the need for public health measures like social distancing or mask-wearing has led to resistance and noncompliance, further complicating efforts to manage the crisis (Ågerfalk et al., 2020; Islam et al., 2020).

To cope with the challenge of widespread misinformation during crises, the role of government is pivotal since the substance of government policies formulated to address the crisis can profoundly influence individuals' comprehension and perspectives, ultimately impacting the dissemination of misinformation (Shirish et al., 2021). This phenomenon can be explained by the Elaboration Likelihood Model (ELM), a well-regarded model in the information systems realm that elucidates how individuals are persuaded by various messages (Petty & Cacioppo, 1986). The ELM posits the central route and the peripheral route as pivotal pathways of persuasion, exerting a significant influence on the effectiveness and impact of public discussions, notably in the sphere of public discourse on government intervention policies (Petty & Cacioppo, 1986; Susmann et al., 2022). Specifically, central-route factors correspond to the content-related arguments and substantive content presented in messages. Inconsistently, peripheral-route factors pertain to publisher-related factors, such as the format of communication content and the cultivation of active participation, serving as superficial cues that stimulate persuasion. Hence, exploring these influential factors behind misinformation diffusion aids policymakers in accurately comprehending the intricacies of misinformation, thereby facilitating the creation of a more reliable information landscape and initiating the inclusion of public opinions in the policymaking process (Bertot et al., 2012).

Despite the cogent reasoning provided in the preceding discussion and the well-established popularity of ELM, current research on misinformation diffusion has predominantly concentrated on cognitive and social-psychological perspectives, overlooking an investigatory viewpoint of information diffusion, particularly with regards to the utilization of ELM (Laato et al., 2020; Miller et al., 2016; Wang et al., 2017; Zhou et al., 2021). Its application in the examination of misinformation related to government intervention policies holds significant promise for advancing the understanding of misinformation through persuasive communication dynamics. Moreover, there has been an oversight concerning the direction of information flow in its implementation. Presently, the majority of research relies on data sourced through government-controlled channels, such as government official accounts, websites, or initiated surveys (Feng et al., 2021; Li & Shang, 2020; Li & Shang, 2023). This one-sided approach to gathering information poses inherent communication barriers since respondents who engage through these channels may exhibit biases, thereby limiting the inclusivity and representativeness of the sampled population (Zimbalist, 2018). Nevertheless, the utilization of social media is promising for acquiring a more comprehensive understanding of the multifaceted perspectives and nuanced viewpoints prevalent within the broader societal fabric.

Therefore, incorporating social media data into research methodologies can potentially enhance the breadth and depth of insights, thus fostering a more inclusive and representative analysis from a citizen-to-authority perspective. Furthermore, the examination of the influence of government management policies on misinformation diffusion remains underexplored when mitigating the misinformation phenomenon amidst a crisis (Dwivedi et al., 2020; George et al., 2021; Laato et al., 2020). Without a comprehensive grasp of the prevailing social discourse and sharing dynamics related surrounding these policies, policymakers may encounter a notable deficit in the requisite insights required for informed policy implementation and effective misinformation management.

To address these gaps, this study investigated the influential factors driving the diffusion of misinformation concerning government management policies from information diffusion perspective. Using COVID-19 as an illustrative example, this study constructed a dataset comprising 144K Twitter [1] posts originating from the UK, spanning from February 2020 to January 2022. Through the lens of the ELM, this study identified central-route factors, proxied by *content topics* and *content similarity*, as well as peripheral-route factors, proxied by *user engagement* (online interaction expressed through followers, likes, comments, and shares) and *message framing* (positive or negative message presentation) (Bonsón & Ratkai, 2013; Feng et al., 2021). With Latent Dirichlet Allocation (LDA) topic modeling (Blei et al., 2003) and regression analysis, the study revealed that user engagement and the discussion frequencies of three specific content topics (face protection, international economic support, and screening methods) exhibit a negative correlation with misinformation diffusion. Content similarity and message framing, however, do not show an association. Additionally, this study checked the impact of government policies, revealing that

[1] Twitter has been rebranded as "X" since July 2023, and this study will continue to use its former name for the sake of familiarity.

containment, economic, and health policies demonstrated a mixed moderating influence in shaping misinformation diffusion, while vaccination policy exhibited no significant impact.

Overall, the study contributes to the literature in the information systems and public policy management fields. Through the perspective of information diffusion, the research has enriched information systems by uncovering diverse patterns in the diffusion of misinformation, with the unique contribution lying in the consideration of social interaction dynamics, which is an aspect that current theories in contemporary misinformation diffusion research have yet to fully explore (Cyr et al., 2018; Feng et al., 2021). Moreover, this study leverages user-generated content (UGC) collected in a manner that highlights the information flow directed back towards authorities from citizens, thereby contributing to the development of two-way communication in government-citizen interactions. Furthermore, the study facilitates the connection of findings in misinformation management research to the field of public policy management. the discovery of diverse moderating effects of government policies offers policymakers customized recommendations and guidelines aimed at enhancing their efficiency when addressing crises (Driss et al., 2019).

4.3 Theoretical Background and Hypotheses Development

4.3.1 Theoretical Background

4.3.1.1 Misinformation Diffusion

The adverse consequences of misinformation diffusion, such as eroded public trust, compromised decision-making, and endangered public health and safety, have propelled scholarly investigations into this phenomenon to prominence in recent years (Islam et al., 2020). The investigations regarding misinformation diffusion have broadly spanned multiple research domains, as detailed in Table 4.1, including cognitive processes, social psychology, political science, and IT infrastructure and digital media. Prevailing theories employed within these domains primarily center on cognitive and psychological fields. The exploration of misinformation diffusion through the perspective of information diffusion remains relatively underdeveloped.

The information diffusion perspective offers a way of looking at how information spreads through social networks (Al-Taie et al., 2017). Being the most classic model in the domain of information diffusion, the ELM distinguishes itself from the aforementioned prevailing theories despite certain connections. Those theories have elucidated the fundamental principles of the ELM through persuasion, and the ELM further extends and elevates these mechanisms to present an information diffusion framework (George et al., 2021). Essentially, central and peripheral routes are two psychological paths to evaluate the persuasiveness of information. Specifically, the central route requires individuals to engage in high-level cognitive processing, entailing critical thinking and in-depth analysis. As a consequence, this route is linked with an evaluation of information content. Conversely, the peripheral route relies on cues demanding low cognitive effort, including superficial indicators or mental shortcuts, for message evaluation. This route is associated with less critical thinking and a more automatic response when sharing information. Despite this acknowledgment, research on misinformation diffusion has yet to directly engaged with the ELM, especially when it comes to public discourse surrounding government intervention policies. Therefore, the overarching objective entails a focused endeavor to directly confront the intricacies of misinformation diffusion, thereby advancing the comprehension of the multifaceted dynamics that underlie this phenomenon.

Table 4.1 Research Domains of Misinformation Diffusion

Research domains	**Theoretical background**	**Recent studies**	**Data explanations**

Cognitive process	Cognitive load theory; health belief model; rational choice theory; theory of motivated reasoning; theory of planned behavior;	(George et al., 2021; Laato et al., 2020; Miller et al., 2016; Wang et al., 2017)	E.g., Laato et al. (2020) conducted an online survey, utilizing validated scales to measure variables: cognitive load factors encompass online information trust and information overload; health beliefs measure perceived susceptibility and severity of ongoing situations; cyberchondria refers to online health searches with a worsening of anxiety or distress
Social psychology	Social support theory; social identity theory; protection motivation theory	(Zhou et al., 2021; George et al., 2021; Laato et al., 2020)	E.g., Zhou et al. (2021) employed social media data to measure variables: informational support refers to whether a given post contains information related to health-related advice, caution, or help-seeking information, labeled as 1 or 0; emotional support is measured by the number of emotional words or terms; ambiguity refers to the number of ambiguous terms; richness categorizes texts by presentation complexity and form, using codes 1, 2, and 3 for text, images, and videos, respectively.
Political science	Theory of motivated reasoning	(Garimella & Eckles, 2020; Miller et al., 2016; Shin et al., 2018)	E.g., Miller et al. (2016) utilized a survey to assess variables: conspiracy endorsement, scored from 0 to 1, reflects the inclination to protect or reinforce one's political worldview; political ideology is categorized on a 7-point scale, ranging from conservative to liberal; knowledge measures an individual's understanding of political topics, quantified from 0 to 1; trust

			refers to respondents' confidence in the reliability of entities like the federal government or the media, ranging from 0 to 1.
IT infrastructure and digital media	Resource-based view; fact-checking	(Schuetz, Sykes, & Venkatesh, 2021)	E.g., Shirish et al. (2021) used report data to formulate variables: mobile connectivity represents the level of mobile internet connectivity, ranging from 1 to 100; economic freedom refers to the fundamental right of individuals to control their own labor and property, ranging from 1 to 5; political freedom relates to the freedom associated with citizens' political choices and participation, ranging from 1 to 7; media freedom refers to the degree of freedom that journalists, news organizations, and netizens enjoy and the efforts made by authorities to ensure this freedom, ranging from 1 to 5.

4.3.1.2 Elaboration Likelihood Model

The ELM addresses how information processing influences decision-making (Petty & Cacioppo, 1986). The model proposes a three-stage process of persuasion: attention, elaboration, and behavior. Initially, it captures public attention. Subsequently, individuals form opinions during the elaboration stage, and these opinions may or may not lead to behavioral changes (Tam & Ho, 2005). In the ELM, central-route features emphasize information-related arguments, often derived from content-related factors, accentuating their relevance (Bhattacherjee & Sanford, 2006; Lee et al., 2017; Shi et al., 2018). Typically, the relevance can be manifested through content topics and content similarity (Feng et al., 2021). Different topics wield varying influences on information diffusion, and similarity tends to affect this process detrimentally (Feng et al., 2021; Stieglitz & Dang-Xuan, 2013; Nagarajan et al., 2010). This relevance can be also manifested within various research contexts. In the case, it is crucial not to overlook the relevance of government management policy. This is because the relevance becomes evident when policies align more closely with individuals' interests, thereby increasing the likelihood of information diffusion (Lee et al., 2017).

Peripheral-route features promote messages relying on superficial factors tied to publishers rather than content (Ji et al., 2019). Usually, seven principles of social influence trigger peripheral features: reciprocity, commitment, consistency, social proof, authority, liking, and scarcity (Cialdini & James, 2009). the study mainly focused on social proof, which describes the phenomenon where people assume that others' actions and words can sway the recipient of new messages, aligning closely with the dynamics of information circulation on social media platforms (Shin, Jian, Driscoll, & Bar, 2018). Particularly, social proof finds expression through user engagement, which can boost information diffusion (Lee et al., 2017; Goh et al., 2013). Additionally, message framing serves as another indicator of social proof, since recipients' propensity to further disseminate messages influenced by their framing, whether positive or negative (Kahneman & Tversky, 2013). It has been predominately observed that negatively framed messages are more effective at promoting diffusion than positively framed ones because they are attention-grabbing and challenge people's expectations (Wu, 2017).

Therefore, the aforementioned contemplation of social interaction dynamics has prompted us to employ the ELM as a theorical lens to investigate misinformation diffusion, leveraging its extensive application in social media communication to provide heuristic insights into the information management domain (Bhattacherjee & Sanford, 2006; Cyr et al., 2018; Li, 2013).

4.3.2 Hypotheses Development

4.3.2.1 Message Framing and Misinformation Diffusion

Message framing has extensively elucidated human decision-making amidst risk, following a value-maximizing standpoint (Kahneman & Tversky, 2013). People tend to be risk-averse or risk-seeking when the outcome of messages is framed with positive or negative connotations, respectively. This is the so-called outcome sensitivities level of message framing. Generally, positive framing underscores positive outcome benefits, while negative framing accentuates adverse consequences.

As per existing literature, negatively framed messages tend to elicit greater public attention and wider distribution than their positively framed counterparts. For example, Goel et al. (2017) discovered that phishing emails aimed at students, highlighting the negative consequences of late registration, were more effective in prompting student responses to fraudulent activities. This phenomenon is attributed to the fact that negatively framed messages, invoking the fear of potential loss, tend to evoke rapid responses driven by impulsive reactions rather than deliberate consideration. However, it has also been observed that positive-framed messages can be more readily embraced than negative-framed ones when discussing opportunities for tuition assistance within phishing emails (Goel et al., 2017). Moreover, positively framed messages sometimes prove ineffective, while only negative messages can restrain the spread of misinformation (Xiao & Benbasat, 2015). This is because positively framed messages do not underscore the potential embedded risks. Consequently, individuals are more inclined to adhere to negatively framed messages, which possess the capability to heighten people's sensitivity to deceptive information, thereby decreasing the probability of disseminating biased messages (Xiao & Benbasat, 2015).

Nonetheless, recent studies indicate that even negatively framed messages might lose their influence in stemming the propagation of misinformed beliefs. Notably, research has observed that when users are exposed to negatively framed messages across six distinct Facebook topics, this does not necessarily lead to an increased or decreased likelihood of generating higher online hits (Ross et al., 2018). Thus, these inconsistencies can be attributed to the notion that the anticipated impact of message framing on information dissemination hinges on contextual factors (Xiao & Benbasat, 2015). It could be argued that factors in highly contextualized messages alter the efficacy of message framing in spreading information.

To gain a more profound understanding of this subject, it is necessary to investigate the influence of message framing on the diffusion of misinformation during a public health crisis. So, this study proposes:

H1.a Positive message framing has a positive impact on the diffusion of misinformation during the COVID-19.

H1.b Negative message framing has a positive impact on the diffusion of misinformation during the COVID-19.

4.3.2.2 User Engagement and Misinformation Diffusion

User engagement involves individuals actively participating in online discussions by expressing thoughts and taking actions (Cegarra-Navarro et al., 2014). Particularly during crises, the transparency and dialogic nature of social media amplify its influence on the spread of (mis)information (Chen et al., 2020; Stone & Can, 2020). Generally, user engagement is measured by multifaceted constructs that incorporate the number of friends, likes, comments, and shares (Bonsón, Royo, & Ratkai, 2015).

Past studies have suggested a potential linkage between user engagement and misinformation diffusion. A high level of user engagement allows individuals to broaden their knowledge, understand responsibilities, and carry out self-organized assistance actions, thereby dispelling rumors (Chen et al., 2020). In addition, stable engagement, such as users' comments or shares, can help maintain trust in public sources, thus avoiding the spread of unnecessary alarmism (Fissi, Gori, & Romolini, 2022). The relationship between user engagement and misinformation diffusion can be explained by the algorithmic power of social media applications. Algorithms interpret increased user engagement as an indication of stronger ties in online informational connections, such as friendships (Leong, 2020). Although online and real-world friendships are separate in the eyes of users, they are indistinguishable within the algorithmic system. This makes it possible for false information to be increasingly visible and spread in online friendships.

Despite numerous studies conducted in this field, the impact of user engagement on misinformation diffusion is still considered a distinct and elusive aspect of information management, particularly with a significant oversight of the crisis context (Chen et al., 2020). Therefore, investigating the impact of user engagement on the spread of misinformation during crises would be valuable in filling this gap and further laying the groundwork for the delivery of accountable public service. So, this study proposes:

H2. User engagement has a negative impact on the diffusion of misinformation during the COVID-19.

4.3.2.3 Content Factors and Misinformation Diffusion

Research has extensively explored content factors, which are information-related arguments, in social media, showcasing their role in spreading information across different contexts (Feng et al., 2021; Hofmann et al., 2013). However, limited attention has been given to misinformation diffusion alongside a specialized examination of content factors. This represents a chance to enhance this field by providing specific strategies for effectively handling particular social events.

Content topics, as a main component of content factors, are worth investigating because they can provide insight into the focus of public attention on the topic that is likely to produce the greatest amount of misinformation dissemination. However, current studies mainly focus on the influence of content topics on general information interaction (L. Li, Tian, Zhang, & Zhou, 2021; Lysyakov, Zhang, & Viswanathan, 2019; Ramanadhan, Mendez, Rao, & Viswanath, 2013). Studies have also shown that no specific type of content topic assures success in terms of the propagation of information in any research context. Consequently, to manage misinformation diffusion, a field-specific review of content topics must be conducted anew.

On the other hand, despite the limited research in this area, content similarity—another vital component of content factors—can significantly contribute to misinformation propagation. Xie (2022) and Feng et al. (2021) found that dissimilarity in social media messages is usually linked to increased message distribution. Such dissimilarity fosters knowledge acquisition, stimulates curiosity, and increased greater public attention, thus promoting a stronger likelihood of information diffusion compared to similar messages (Feng et al., 2021; Gu et al., 2014; Xie, 2022). However, a minority perspective posits that content similarity might correlate with a higher diffusion probability, facilitated by its simplicity in duplication and forwarding (Barbosa, Cesar-Jr, & Cosley, 2015). This inconsistency can be clarified by the discovery that the timing of social relationship formation impacts content dynamics. Similar content usually gains popularity shortly after the relationship forms, while dissimilar content progressively gains dominance thereafter (Zeng & Wei, 2013).

Hence, to attain a more comprehensive understanding of how content factors contribute to the spread of misinformation, this study proposes:

H3.a Different content topics have varying impacts on the diffusion of misinformation during the

COVID-19.

H3.b Content similarity has a negative impact on the diffusion of misinformation during the COVID-19.

4.3.2.4 Moderating Effects of Government Policies on Misinformation Diffusion

In the recent surge in social media use, governments have leveraged this platform to convey crisis management policies, altering the distribution of (mis)information. No longer content with passivity, citizens are increasingly voicing their personal opinions about these policies on social media platforms (Bonsón et al., 2012). Apart from direct interactions on official government-controlled channels, policymakers often remain oblivious to citizens' opinions and neglect engagement with these viewpoints for policy refinement. Consequently, a significant source of grassroots insights into newly devised policies remains unutilized, leading to adverse effects on policy enhancement and local service provision (Ramon Gil-Garcia et al., 2007).

Previous research has suggested the potential divergent effects of government policies on misinformation propagation, stemming from different policy types. Governments commonly employ two approaches for policy implementation: stick and sermon (Bemelmans-Videc et al., 2017). Stick policies involve absolute authoritative government enforcement, often with one-way policy information transmission, while sermon policies promote interactive information exchange between governments and citizens, fostering two-way risk communication (TWRC). Through the operation of TWRC, citizens are provided with avenues to voice their opinions and engage in broader discussions related to specific policies. This facilitates citizen-government interactions through the exchange of scientific information or knowledge, which can assist citizens in surpassing cognitive limitations and comprehending policy objectives (Guan et al., 2021; Weaver, 2014). Conversely, stick policies frequently result in information gaps, failing to address misinterpretations and thereby exacerbating the spread of misinformation (Li, 2020).

To elaborate further, different policy types exhibit diverse levels of information richness, which serves as a moderating factor in the relationship between the content attributes of messages and their diffusion across information system platforms (Li et al., 2022; Zhou et al., 2021). This augmented information richness can alleviate uncertainty and elucidate ambiguity in content, thereby increasing the likelihood of users forwarding messages to extend their social influence (Daft & Lengel, 1983; Yin et al., 2018). Accordingly, it can be inferred that the influence of content-related factors on the diffusion of misinformation can be subject to diverse moderation by government policies, contingent upon the degree of their information richness. However, an explicit examination of this underlying effect has not been undertaken in the literature. this study therefore extended previous studies and explored this effect in the context of the COVID-19 pandemic. Considering that government management policies are broadly classified into four categories: containment, economics, health, and vaccination (Hale et al., 2020), this study proposes:

H4.a Containment policy has moderating effects on the relationship between different content factors and the diffusion of misinformation during the COVID-19.

H4.b Economic policy has moderating effects on the relationship between different content factors and the diffusion of misinformation during the COVID-19.

H4.c Health policy has moderating effects on the relationship between different content factors and the diffusion of misinformation during the COVID-19.

H4.d Vaccination policy has moderating effects on the relationship between different content factors and the diffusion of misinformation during the COVID-19.

Figure 4.1 illustrates the conceptual model depicting the interconnections among various variables.

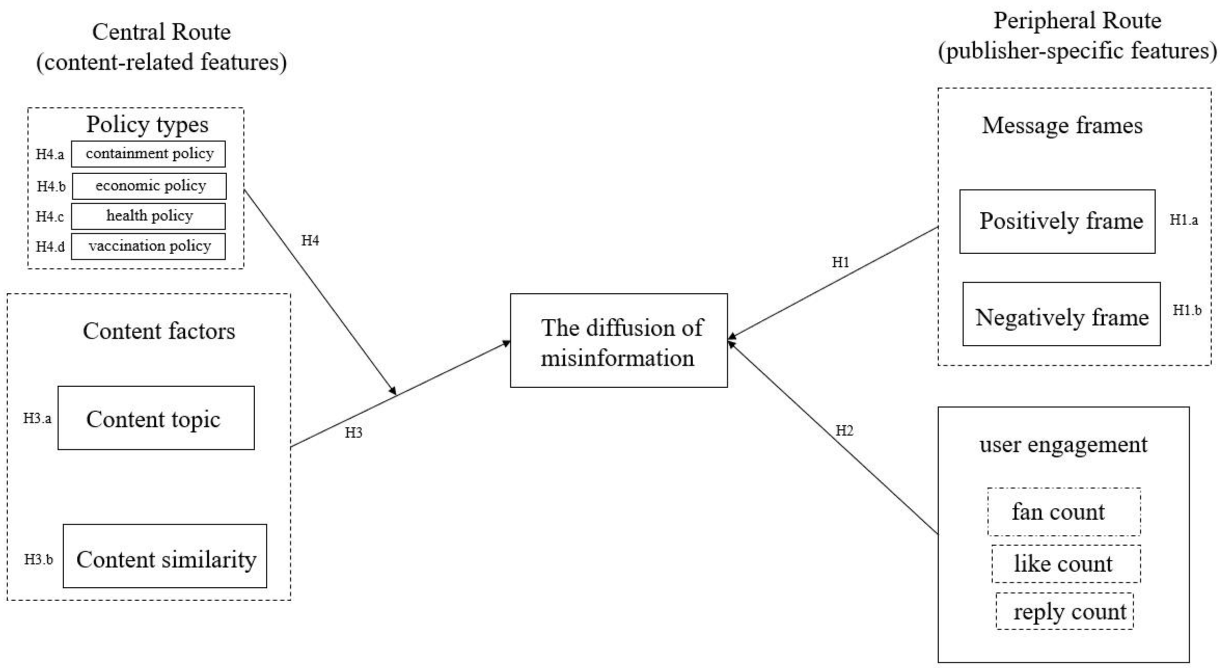


Figure 4.1 The Conceptual Framework

4.4 Methodology

4.4.1 Data Collection and Preprocessing

Various COVID-19 management policies, tracked by the Oxford COVID-19 Government Response Tracker (OxCGRT) project, were broadly categorized into four groups: containment, economic, health, and vaccination (Hale, Webster, Petherick, Phillips, & Kira, 2020). The project additionally provides a set of keywords associated with each policy, facilitating the collection of related tweets (as demonstrated in Table 4.2). Subsequently, this study employed the Twitter API to retrieve 1.2 million policy-related tweets spanning from February 2020 to January 2022. This data also included geolocations, follower counts, likes, comments, retweets, and hashtags.

Considering the study's UK-centric scope, further filtering was required. this study employed the pycountry package (pycountry, 2022) to retrieve valid country names and used world city data (DataHub, 2018) to map city names to source countries. For cities matching multiple countries, this study assigned them to the country with the highest population, assuming that larger cities would more likely omit country identifiers (Chum et al., 2021). This increased geolocation data availability from 18.7% to 61%, resulting in a cleaned dataset of 144K UK tweets from February 2020 to January 2022. Finally, this study kept English-only tweets, converted text to lowercase, removed HTML tags, @usernames, numbers, punctuation, special characters, and stop words, and tokenized the content.

Table 4.2 Keywords by Government Policy Type

Government policies	OxCGRT keywords
Containment	School closure, work from home, cancel event, gathering ban, transport ban, stay at home, travel ban
Economic	Income support, debt relief, economic stimulus, international support
Health	Health campaign, PCR, contact tracing, health investment, face mask, protect elderly
Vaccination	Vaccine priority, vaccine available, vaccine investment

4.4.2 Measures

The hypothesis testing incorporated four types of independent variables, one dependent variable, and two control variables, as per the conceptual framework (Figure 4.1).

4.4.2.1 Independent Variables

First, user engagement was calculated using Bonsón, Royo, and Ratkai (2015) engagement metric (see Table 4.3), including likes (popularity), comments (commitment), and shares (virality). These indicators are independent of audience size, so they are the most representative measures of user engagement.

Table 4.3 The Metrics for User Engagement

Metrics	Formula	Description
Popularity	P1 Number of posts liked/total posts	Percentage of posts that have been liked
	P2 Total likes/total posts	Average number of likes per post
	P3 (P2/number of fans) × 1000	Average number of likes per post per 1000

		fans
Commitment	C1 Number of posts commented/total posts	Percentage of posts that have been commented
	C2 Total comments/total posts	Average number of comments per post
	C3 (C2/number of fans) × 1000	Average number of comments per post per 1000 fans
Virality	V1 Number of posts shared/total posts	Percentage of posts that have been shared
	V2 Total shares/total posts	Average number of shares per post
	V3 (V2/number of fans) × 1000	Average number of shares per post per 1000 fans
User engagement	E P3 + C3 + V3	Shareholder engagement index

Second, message framing was measured by sentiment polarity using the Python TextBlob package (textblob, 2022). While message framing appears to be a visible structure of messages and emotion is a hidden status, previous research has revealed the predictive power of the emotions-as-frames approach in measuring message framing, validating sentiment's utility in its measurement (Nabi et al., 2020).

Third, the content factors contain two components: content topics and content similarity. Content topics were extracted using the Python LDA package, a topic modeling technique, to streamline extraction across four policy types (containment, economic, health, and vaccination). LDA calculates word-topic probabilities and estimates the likelihood of a document containing a specific topic (Blei et al., 2003). Subsequently, the coherence score was then utilized to determine the optimal number of topics, measuring semantic similarity between high-scoring terms within a topic, thereby representing LDA model performance (higher scores indicate better performance, as detailed in Appendix 4). Content similarity refers to the resemblance of a tweet to other tweets (Feng, Hui, Deng, & Jiang, 2021). It was measured by calculating the cosine similarity of the term frequency-inverse document frequency (TF-IDF) vectors of all tweets. Assuming the TF-IDF vectors of two tweets x and y, denoted as $\overrightarrow{t_x}$ and $\overrightarrow{t_y}$, the similarity $sim\ (\overrightarrow{t_x}, \overrightarrow{t_y})$ between x and y is computed as follows:

$$sim\left(\overrightarrow{t_x}, \overrightarrow{t_y}\right) = \frac{\overrightarrow{t_x} \cdot \overrightarrow{t_y}}{\|\overrightarrow{t_x}\| \cdot \|\overrightarrow{t_y}\|}\ , \tag{4.1}$$

where $\| \overrightarrow{t_x} \|$ and $\| \overrightarrow{t_y} \|$ represents the length of $\overrightarrow{t_x}$ and $\overrightarrow{t_y}$. The aggregate homogeneity of a given post i is represented as the average similarity between i and all other tweets j published in the same month as:

$$similarity\left(\overrightarrow{t_i}\right) = \frac{1}{k}\sum\nolimits_{\overrightarrow{t_j} \in M(\overrightarrow{t_i})} sim(\overrightarrow{t_i}, \overrightarrow{t_j})\ , \tag{4.2}$$

where similarity $(\overrightarrow{t_i})$ represents the homogeneity of tweet i, k is the number of tweets, j ranges from 1 to k, $M\ (\overrightarrow{t_i})$ denotes the set of tweets published in the same month as tweet i, and $\overrightarrow{t_i} \in M\ (\overrightarrow{t_i})$.

Fourth, the policy variable indicates the overall stringency of each policy type. This variable stems from the OxCGRT project (Hale et al., 2020).

4.4.2.2 Dependent Variable

The diffusion of misinformation is typically measured through Twitter's retweeting feature, a robust mechanism for information sharing (Stieglitz & Dang-Xuan, 2013). To assess misinformation diffusion, identifying misinformed tweets is imperative. To achieve this, a classification model was constructed utilizing the COVID-19 Fake News Detection dataset, with a detailed example in Appendix 2. This balanced dataset, widely utilized, comprises manually annotated and fact-checked Twitter posts. It encompasses misinformed tweets aligned with the defined misinformation criteria (Patwa et al., 2021). Specifically, the dataset encompassed 3,360 tweets classified as non-misinformation and 3,060 as misinformation. Prior to final classification, model selection employed

80% of the dataset for training and the remaining 20% for validation. The optimal precision, recall, and F-1 scores were achieved with a logistic regression classifier at 92%, 97%, and 94%, respectively. This model was then applied to classify the unlabeled tweets. The diffusion of misinformation was measured by the daily percentage of retweets for misinformed posts.

4.4.2.3 Control Variables

This study examined two types of control variables that could influence misinformation diffusion: semantic variables and COVID-19 variant phases. Semantic variables contain counts of emoticons, external links, mentions of others, hashtags, and images (Feng et al., 2021). COVID-19 variant phases include Alpha, Beta, Gamma, Delta, and Omicron (WHO, 2022).

4.5 Findings

4.5.1 Results of Topic Modeling and Descriptive Statistics of Data

Based on coherence scores, an initial set of 26 topics was identified. To enhance clarity, topics were then labeled inductively by looking at a topic's most important keywords and the tweets associated with the topic. This refinement yielded 13 comprehensive topics, with detailed explanations and distribution plots in Appendix 5.

Specifically, content topic 1 depicts changes in people's daily routines. Its distribution visualization indicates its peak popularity during the initial stages of the pandemic, highlighting its more immediate and direct influence at that time. Content topic 2 illustrates the citizen-government relationship. Its moving trend resembles that of content topic 1, reflecting the substantial influence of altered daily routines on this relationship. The primary focus of content topic 3 is international economic support, which varied during the pandemic, with a noticeable surge at the onset. Content topic 4 displays employment assistance plans. References to HM Revenue and Customs and the

Self-Employment Income Support Scheme grant indicate heightened concerns about grant applications and necessary claims, as revealed by the two initial peaks in the plot. The theme of content topic 5 is national economic support. This topic did not peak immediately after the pandemic began because individuals still had financial resources, but gradually grew in popularity and peaked around July 2020. Content topic 6 concerns face coverings, with discussions cantering around the level of protection they offered, and it peaked early in the pandemic. Content topic 7 discusses infection and death, peaking in late 2020 and early 2021, corresponding with official statistics data (GOV, 2022). Content topic 8 focuses on physical feelings and symptoms, most notably during the Omicron variant phase. Content topic 9 underscores the quality of screening services, which peaked around September 2021, coinciding with the emergence of the Delta variant (WHO, 2022). Content topic 10 showcases outcomes from testing operations, primarily involving PCR and lateral flow tests. This topic peaked early in 2022 when schools were trying to reopen. Content topic 11 revolves around safeguarding the elderly, a prominent theme throughout the pandemic. Content topic 12 delineates the vaccine rollout, peaking after the landmark moment of the first NHS patient receiving the vaccine in early December 2020 (NHS, 2020). With a similar distribution trend, content topic 13 displays the public's desire for future vaccination development.

Then, this study performed descriptive statistics and Pearson correlation analysis after preliminary processing (Tables 4.4 and Appendix 6). To investigate potential multicollinearity, the variance inflation factor (VIF) of each variable was inspected, with the highest VIF being 9.13, below the threshold of 10 (Aiken et al., 1991), signifying no significant multicollinearity impact.

Table 4.4 Descriptive Statistics

Variables		Mean	Std. Dev.	Min	Max	VIF
Control variables						
1	Hashtag	254.48	367.04	0	6193	5.85
2	Emoticons	1.25	3.07	0	35	1.08
3	Outlinks	133.11	80.73	0	918	9.13

4	At	195.41	122.45	0	910	6.85
5	Images	0.18	0.50	0	6	1.03
6	Alpha	0.13	0.33	0	1	3.46
7	Beta	0.09	0.28	0	1	1.86
8	Gamma	0.14	0.35	0	1	2.30
9	Delta	0.28	0.45	0	1	2.10
10	Omicron	0.09	0.28	0	1	4.15
11	User engagement	0.001	0.002	0	0.025	1.04
12	Positive message framing	113.49	71.15	0	780	7.57
13	Negative message framing	84.98	58.09	0	713	7.57
14	Content similarity	0.02	0.01	0.01	0.09	1.04
15	Content topic 1	22.51	56.75	0	1071	3.82
16	Content topic 2	2.05	7.28	0	158	3.02
17	Content topic 3	3.54	4.40	0	46	1.88
18	Content topic 4	1.75	6.51	0	128	1.55
19	Content topic 5	1.08	2.24	0	36	1.49
20	Content topic 6	20.81	19.06	0	328	1.56
21	Content topic 7	31.09	27.35	0	177	3.46
22	Content topic 8	25.32	39.10	0	279	5.41
23	Content topic 9	12.78	28.09	0	679	3.89
24	Content topic 10	10.61	16.22	0	262	4.22
25	Content topic 11	10.60	6.52	0	61	2.17
26	Content topic 12	34.59	32.00	0	368	4.25
27	Content topic 13	9.97	14.11	0	98	2.50
28	Containment policy strictness	56.19	19.11	0	86.46	1.93
29	Economic policy strictness	82.91	32.66	0	100	2.13
30	Health policy strictness	65.51	11.89	22.22	76.39	2.70
31	Vaccination policy strictness	47.48	41.39	0	100	3.23
32	Misinformation (%)	0.49	0.25	0.37	0.63	1.02

4.5.2 Results of Misinformation Classification

The outcomes from the pre-trained classification model indicated that misinformation outnumbered non-misinformation throughout the sample period. This aligns with prior research that states that misinformation has a greater reach than the truth (Garimella & Eckles, 2020; Vosoughi, Roy, & Aral, 2018).

Moreover, Figure 4.2 shows that the introduction of government management policies has potentially mitigated misinformation diffusion. After introducing a new policy, the public might necessitate extra time for information processing and social media deliberations. Consequently, rather than yielding an immediate reduction in misinformation, a gradual decrease in misinformation levels might occur afterward.

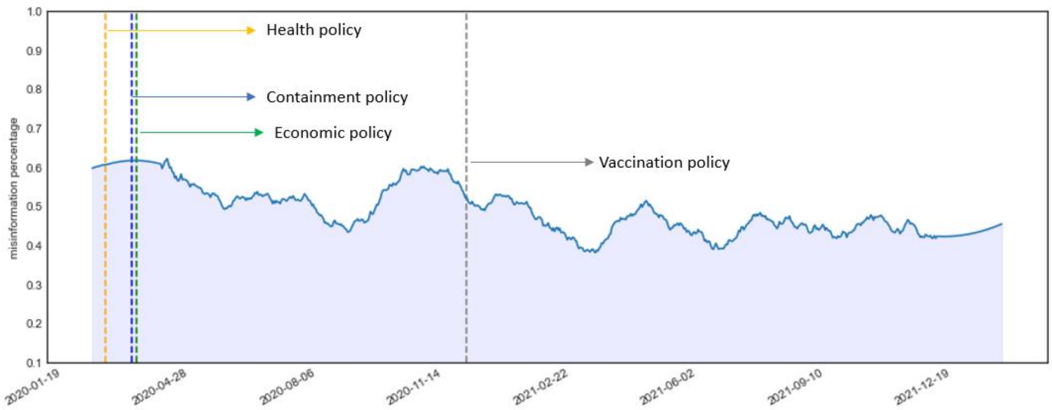


Figure 4.2 The Evolution of Misinformation

3.5.3 Results of Regression Analysis

Ordinary least squares (OLS) regression analysis was employed to estimate the relationship between the independent variables and misinformation diffusion, with the results shown in Table 4.5. Model 1 comprises control variables only; Model 2 includes message framing; Model 3 incorporates user engagement; Model 4 covers content factors; and Model 5 encompasses all variables. Table 4.6 shows the findings of the moderation effect, with each model examining the moderating effect of each policy. Figure 4.3 demonstrates the robustness of the models by illustrating that residuals can be represented by a normal distribution curve: (a) Histogram of residuals of Model 5; (b) P-P curve of residuals.

Model 2 shows that the coefficients of both positive and negative message framing are not significant, indicating non-support for hypotheses H1.a and H1.b. While message framing undoubtedly plays an important role in spreading information, it is not the decisive factor in the diffusion of misinformation, which can also be influenced by various other factors. In Model 3, the significant coefficient of user engagement confirms H2. User engagement negatively influences the diffusion of misinformation, implying that misinformed messages are less likely to propagate on social media as more individuals engage. In Model 4.1, significant coefficients for content topics 3 (international economic support), 6 (face coverings), and 10 (school screening methods) are negatively linked to misinformation diffusion, validating H3.a. However, the coefficient for content similarity in Model 4.2 is not significant, thereby not supporting H3.b. Lastly, from the perspective of the model's fit, Model 5 demonstrates that the addition of all the independent variables resulted in an increase in the fitting degree (R^2), substantiating the validity of the proposed model.

Table 4.5 Regression Analysis

Variables	**Model 1**	**Model 2**		**Model 3**	**Model 4**		**Model 5**
		Model 2.1	**Model 2.2**		**Model 4.1**	**Model 4.2**	
Constant	0.031 (0.207)	0.021 (0.208)	0.024 (0.209)	-0.005 (0.207)	0.583** (0.247)	0.701 (0.234)	0.522** (0.249)
Control variables							
Hashtag	0.177 (0.119)	0.196* (0.121)	0.180 (0.119)	0.029 (0.133)	0.030 (0.025)	0.010 (0.022)	0.013 (0.025)
Emoticons	-0.010 (0.020)	-0.007 (0.020)	-0.009 (0.020)	-0.013 (0.020)	0.026 (0.016)	0.017 (0.016)	0.023 (0.016)
Outlinks	0.513** (0.207)	0.537** (0.209)	0.522** (0.209)	0.440** (0.208)	0.048 (0.044)	0.016 (0.036)	0.035 (0.067)
At	0.055 (0.139)	0.072 (0.141)	0.065 (0.143)	0.091 (0.140)	0.010 (0.032)	0.016 (0.027)	0.005 (0.037)
Images	0.025 (0.019)	0.027 (0.019)	0.025 (0.019)	0.027 (0.019)	0.023 (0.019)	0.023 (0.019)	0.026 (0.019)
Alpha	0.076 (0.072)	0.094 (0.074)	0.083 (0.075)	0.078 (0.071)	0.143** (0.084)	0.204** (0.079)	0.147* (0.084)
Beta	0.094* (0.052)	0.083 (0.054)	0.089 (0.055)	0.089 (0.052)	0.180** (0.071)	0.184*** (0.059)	0.165* (0.071)
Gamma	-0.016 (0.048)	-0.032 (0.051)	-0.023 (0.053)	-0.026 (0.048)	0.066 (0.060)	0.083 (0.051)	0.053 (0.06)
Delta	-0.093 (0.074)	-0.104 (0.075)	-0.099* (0.076)	-0.111 (0.074)	0.017 (0.082)	0.020 (0.076)	-0.013 (0.083)
Omicron	-0.091 (0.084)	-0.089 (0.084)	-0.092 (0.084)	-0.100 (0.084)	0.038 (0.092)	0.015 (0.088)	0.021 (0.092)

Independent variables							
Positive message framing		-0.023 (0.025)					-0.025 (0.067)
Negative message framing			-0.007 (0.024)				0.022 (0.052)
User engagement				-0.024*** (0.01)			-0.031*** (0.009)
Content similarity						0.045 (0.259)	0.045 (0.062)
Content topic 1					-0.017 (0.017)		-0.011 (0.017)
Content topic 2					-0.005 (0.023)		0.004 (0.023)
Content topic 3					-0.029* (0.016)		-0.027* (0.016)
Content topic 4					0.020 (0.017)		0.020 (0.017)
Content topic 5					0.006 (0.021)		0.008 (0.021)
Content topic 6					-0.037* (0.020)		-0.036* (0.02)
Content topic 7					0.030 (0.025)		0.027 (0.026)
Content topic 8					0.003 (0.021)		0.007 (0.022)
Content topic 9					-0.012 (0.019)		-0.007 (0.019)
Content topic 10					-0.034* (0.018)		-0.032* (0.018)
Content topic 11					0.002 (0.022)		0.009 (0.022)
Content topic 12					-0.027 (0.025)		-0.021 (0.025)
Content topic 13					-0.007 (0.015)		-0.006 (0.015)
R^2	0.08	0.08	0.08	0.09	0.09	0.06	0.12
F	4.53***	4.22***	4.53***	4.65***	2.17***	2.99***	2.40***
Note: $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$; Standard errors are reported in parentheses.							

Furthermore, this study included interactive product terms as predictors to test the moderation effects of policies (Table 4.6). Model 6.1 shows that the containment policy moderates the relationship between content topics (topic 1: daily routines; topic 2: citizen-government relationships; topic 4: employment assistance; topic 12: vaccines) and misinformation diffusion. Specifically, the introduction of the containment policy reduces misinformation diffusion by either strengthening the negative impact of topics 1 and 12 or weakening the positive influence of topics 2 and 4, thereby supporting Hypothesis 4a. In line with Model 6.2, the economic policy moderates the relationship between content topics (topic 5: national economic support, topic 12: vaccines) and misinformation diffusion. This suggests that leveraging economic policy to strengthen the inverse relationship between these topics and misinformation can effectively reduce its spread, confirming H4.b. Supported by significant positive coefficients of interaction terms in Model 6.3, the health policy strengthens the negative relationship between content topics (topic 4: employment assistance plans, topic 6: face coverings) and misinformation diffusion, affirming H4.c. H4.d is not supported, since no interaction terms are significant in Model 6.4.

Table 4.6 Moderation Analysis

Variables	**Model 6**			
	Model 6.1	Model 6.2	Model 6.3	Model 6.4
Constant	-0.157 (0.555)	0.248 (0.426)	0.085 (0.469)	0.158 (0.586)
Control variables				
Hashtag	0.185 (0.123)	0.194 (0.121)	0.150 (0.130)	0.254** (0.126)
Emoticons	0.003 (0.021)	0.004 (0.021)	-0.007 (0.021)	-0.010 (0.021)
Outlinks	0.612*** (0.223)	0.552*** (0.213)	0.723*** (0.274)	0.573** (0.238)
At	0.117 (0.148)	0.112 (0.146)	0.271 (0.163)	0.149 (0.154)
Images	0.024 (0.019)	0.031 (0.019)	0.018 (0.019)	0.017 (0.019)
Alpha	0.010 (0.054)	0.008 (0.054)	-0.055 (0.057)	-0.035 (0.056)

Beta	0.005 (0.131)	0.000 (0.126)	-0.037 (0.132)	-0.061 (0.129)
Gamma	-0.077 (0.123)	-0.085 (0.119)	-0.103 (0.128)	-0.143 (0.121)
Delta	-0.139 (0.153)	-0.129 (0.147)	-0.164 (0.152)	-0.188 (0.147)
Omicron	-0.095 (0.161)	-0.107 (0.153)	-0.123 (0.159)	-0.166 (0.153)
Independent variables				
Content similarity	-0.031 (0.119)	0.031 (0.084)	0.044 (0.211)	0.036 (0.143)
Content topic 1	-0.062 (0.060)	0.002 (0.022)	0.030 (0.105)	-0.067 (0.057)
Content topic 2	0.097 (0.079)	0.024 (0.045)	-0.001 (0.150)	0.083 (0.076)
Content topic 3	-0.021 (0.035)	-0.090* (0.050)	0.099 (0.125)	-0.131* (0.067)
Content topic 4	0.111** (0.049)	0.060 (0.059)	-0.218 (0.143)	0.051 (0.061)
Content topic 5	0.063 (0.064)	-0.223*** (0.085)	0.143 (0.191)	-0.004 (0.070)
Content topic 6	-0.041 (0.035)	-0.030 (0.028)	-0.387*** (0.120)	-0.017 (0.065)
Content topic 7	0.079** (0.043)	0.042 (0.034)	0.019 (0.133)	-0.042 (0.079)
Content topic 8	-0.017 (0.040)	0.019 (0.035)	0.008 (0.144)	-0.029 (0.069)
Content topic 9	0.026 (0.040)	0.028 (0.032)	0.055 (0.134)	0.097 (0.073)
Content topic 10	-0.022 (0.041)	-0.043 (0.032)	0.076 (0.143)	0.005 (0.066)
Content topic 11	-0.036 (0.043)	0.002 (0.032)	0.113 (0.126)	0.079 (0.079)
Content topic 12	-0.093* (0.049)	-0.082** (0.038)	-0.173 (0.133)	0.007 (0.116)
Content topic 13	0.018 (0.029)	0.007 (0.023)	0.065 (0.105)	0.103 (0.072)
Containment policy strictness	0.049 (0.226)			
Economic policy strictness		-0.059 (0.262)		
Health policy strictness			-0.046 (0.182)	

Vaccination policy strictness				-0.364* (0.198)
Containment policy strictness * content similarity	0.021 (0.054)			
Containment policy strictness * content topic 1	0.025* (0.014)			
Containment policy strictness * content topic 2	-0.038* (0.023)			
Containment policy strictness * content topic 3	-0.003 (0.014)			
Containment policy strictness * content topic 4	-0.026* (0.014)			
Containment policy strictness * content topic 5	-0.017 (0.020)			
Containment policy strictness * content topic 6	0.010 (0.015)			
Containment policy strictness * content topic 7	-0.019 (0.015)			
Containment policy strictness * content topic 8	0.006 (0.014)			
Containment policy strictness * content topic 9	-0.011 (0.014)			
Containment policy strictness * content topic 10	-0.004 (0.015)			
Containment policy strictness * content topic 11	0.018 (0.016)			
Containment policy strictness * content topic 12	0.032* (0.018)			
Containment policy strictness * content topic 13	-0.009 (0.012)			
Economic policy strictness * content similarity		-0.026 (0.058)		
Economic policy strictness * content topic 1		-0.010 (0.016)		
Economic policy strictness * content topic 2		-0.008 (0.024)		
Economic policy strictness * content topic 3		-0.002 (0.018)		
Economic policy strictness * content topic 4		-0.030 (0.020)		
Economic policy strictness * content topic 5		0.076** (0.031)		
Economic policy strictness * content topic 6		0.008 (0.018)		

Economic policy strictness * content topic 7		-0.008 (0.018)		
Economic policy strictness * content topic 8		-0.012 (0.019)		
Economic policy strictness * content topic 9		-0.024 (0.018)		
Economic policy strictness * content topic 10		0.004 (0.017)		
Economic policy strictness * content topic 11		0.008 (0.021)		
Economic policy strictness * content topic 12		0.045** (0.020)		
Economic policy strictness * content topic 13		-0.006 (0.013)		
Health policy strictness * content similarity			-0.022 (0.050)	
Health policy strictness * content topic 1			-0.008 (0.022)	
Health policy strictness * content topic 2			-0.002 (0.033)	
Health policy strictness * content topic 3			-0.028 (0.027)	
Health policy strictness * content topic 4			0.054* (0.033)	
Health policy strictness * content topic 5			-0.032 (0.043)	
Health policy strictness * content topic 6			0.070*** (0.023)	
Health policy strictness * content topic 7			-0.003 (0.030)	
Health policy strictness * content topic 8			-0.005 (0.033)	
Health policy strictness * content topic 9			-0.016 (0.029)	
Health policy strictness * content topic 10			-0.025 (0.031)	
Health policy strictness * content topic 11			-0.028 (0.027)	
Health policy strictness * content topic 12			0.038 (0.030)	
Health policy strictness * content topic 13			-0.014 (0.022)	
Vaccination policy strictness * content similarity				-0.046 (0.043)

Vaccination policy strictness * content topic 1				0.018 (0.016)
Vaccination policy strictness * content topic 2				-0.025 (0.021)
Vaccination policy strictness * content topic 3				0.028 (0.019)
Vaccination policy strictness * content topic 4				-0.009 (0.019)
Vaccination policy strictness * content topic 5				0.005 (0.020)
Vaccination policy strictness * content topic 6				0.001 (0.018)
Vaccination policy strictness * content topic 7				0.023 (0.024)
Vaccination policy strictness * content topic 8				0.012 (0.021)
Vaccination policy strictness * content topic 9				-0.026 (0.021)
Vaccination policy strictness * content topic 10				-0.008 (0.018)
Vaccination policy strictness * content topic 11				-0.022 (0.023)
Vaccination policy strictness * content topic 12				0.025 (0.021)
Vaccination policy strictness * content topic 13				-0.024 (0.018)
R^2	0.123	0.126	0.128	0.127
F	1.994***	2.064***	2.130***	1.890***
Note: *p < .1, **p < .05, ***p < .01; Standard errors are reported in parentheses.				

Lastly, Figure 4.3 displays the robustness check of the models. The two subfigures depict the normal distribution pattern of the OLS model residuals: (a) a histogram of Model 5 residuals and (b) a P-P curve of residuals, plotting the empirical cumulative distribution against the theoretical cumulative distribution of a normal distribution.

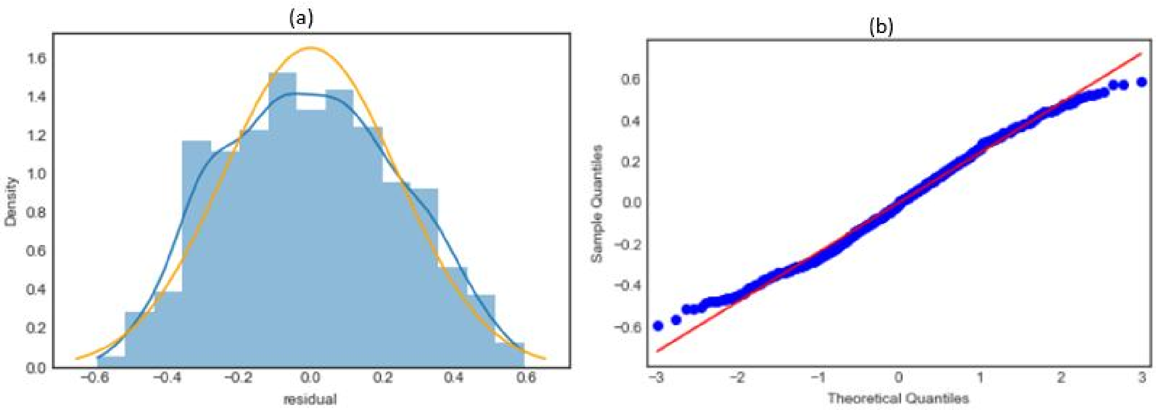


Figure 4.3 Robustness Check

4.6 Discussion and Contribution

4.6.1 Main Findings

The study tackles the pressing concern of misinformation diffusion in the digital media realm, aiming to bridge the gap by integrating social media feedback into information management and policy decision-making (Bertot et al., 2012; Shirish et al., 2021). The key findings are summarised as follows.

First, user engagement is negatively linked to misinformation diffusion via the peripheral route. This contrasts with previous research indicating that heightened user engagement typically aligns with greater dissemination of general information (Cyr, Head, Lim, & Stibe, 2018; Feng et al., 2021). Additionally, despite the usual importance of message framing in the dissemination of general information, it had an insignificant effect on shaping misinformation diffusion (Price, Nir, & Cappella, 2005; Xiao & Benbasat, 2015).

Second, through the central route, content similarity does not influence misinformation diffusion, contradicting earlier research that suggested its negative impact (Feng et al., 2021). This discrepancy highlights the potential divergences between misinformation diffusion and general information dissemination dynamics. Besides, the study identifies three content topics associated with reduced misinformation diffusion: topic 3 (international economic support), topic 6 (face coverings), and topic 10 (screening methods).

Third, this study explored the moderating impact of government management policies. Containment, economic, and health policies positively moderate the relationship between content factors and misinformation diffusion, while vaccine policy does not.

4.6.2 Theoretical Contributions

This study yields implications for future research on misinformation diffusion and public policy management during global disruptions and crises.

First, by conducting an examination of misinformation diffusion through the lens of ELM, the research has enriched the landscape of information diffusion research by uncovering diverse diffusion patterns in misinformation and considering social interaction dynamics at the information diffusion level. For example, the discovery of a negative correlation between user engagement and misinformation diffusion challenges prior findings, implying that users possess the inherent capability to discern inaccuracies within online content, prompting a reassessment of citizen-government dynamics (Cyr et al., 2018; Feng et al., 2021). The inconsistent findings on content similarity also provide an opportunity to mitigate misinformation diffusion by shifting away from the previous emphasis on dissimilar online messages (Feng et al., 2021). Meanwhile, this study has advanced the understanding of misinformation diffusion by comprehensively considering the social interaction dynamics. Compared with prevailing theories employed within prior research domains, as detailed in Table 4.1, the application of ELM inherently incorporates the structure of online communication networks, a pivotal element in the spread of information, including misinformation (Petty & Cacioppo, 1986). Consequently, this study can yield more straightforward and well-informed strategies for mitigating misinformation diffusion. Further, misinformation spreads widely because of social and network dynamics such as peer endorsement, propagation by social influencers, and interactive user comments, all of which are considered in the propagation process and lead to amplification (George et al., 2021). The ELM accounts for these social amplification processes, shedding light on how misinformation can rapidly proliferate within communities and networks (Bonsón et al., 2015). Lastly, given the prevalence of misinformation circulating within social contexts, the focus on information diffusion appears to be better aligned with the real-world dynamics of online communication (Wang et al., 2021). This approach captures sociocultural aspects often overlooked previously, offering more applicable recommendations for tackling contemporary challenges associated with misinformation on social media and digital channels. Overall, the work would contribute fresh insights to the evolving literature on information system management.

Second, the study leverages UGC collected in a manner that highlights previously overlooked aspects of information flow direction within the ELM. This approach facilitates the establishment of a citizen-to-authority perspective, thereby contributing to the development of two-way communication in government-citizen interactions. Presently, authorities employ one-way communication channels for the direct collection of citizens' opinions, typically through government official accounts, websites, or initiated surveys (Feng et al., 2021; Li & Shang, 2020; Li & Shang, 2023). However, citizens often prefer inclusive online environments with diverse stakeholder groups for expressing their opinions, potentially leading policymakers to inadvertently overlook vital insights crucial for government-citizen communication. Facing this challenge, incorporating UGC can effectively facilitate two-way communication (Nisar et al., 2018). UGC on social media platforms inherently fosters citizen empowerment, enabling diversified feedback and perspectives on government policies (Kar & Dwivedi, 2020). This engagement allows policymakers to gather valuable insights to inform their decisions while mitigating misinformation and preserving information integrity. Additionally, engaging with UGC promotes transparency and trust (Zhang, Zhao, & Gupta, 2018). Open dialogues between policymakers and citizens enhance information credibility and convey a commitment to public receptiveness, thereby effectively countering misinformation. In light of these considerations, this study can offer authorities additional citizen-derived insights while managing misinformation, which may be challenging when viewed from the opposite perspective.

Third, the study enriches public policy management by connecting the potential influence of government policies to misinformation diffusion. Specifically, this study confirmed the roles played by stick and sermon policies. the findings reveal that containment, economic, and health policies can shape misinformation diffusion, contrasting the scenario with vaccination policy. This distinction finds its roots in the argument that the former three policies align with the nature of sermon policies, fostering a heightened information richness and subsequently impacting misinformation diffusion dynamics. Conversely, the vaccination policy, akin to a stick approach, is enforced rigorously, effectively constraining the opportunity for bilateral discourse and ultimately yielding negligible impact on misinformation diffusion (Duch et al., 2021; Iguacel et al., 2022). Recognizing that, valuable insights can be provided into the policymaking process. Central to policymaking, a loop of modeling and policy cycles encompasses a series of ordered tasks (Driss et al., 2019), illustrated in Figure 4.4. Within the policy cycle, this study added values into the evaluation task, informed by an understanding of the varied moderating effects of policies. This contribution can guide policy adjustments to mitigate unintended consequences of crisis management, such as misinformation diffusion. In the modelling cycle, this study introduced a fresh perspective to the data collection task by considering data retrieval from citizens in crisis situations, thus broadening the research scope for comprehensive misinformation diffusion management across diverse contexts.

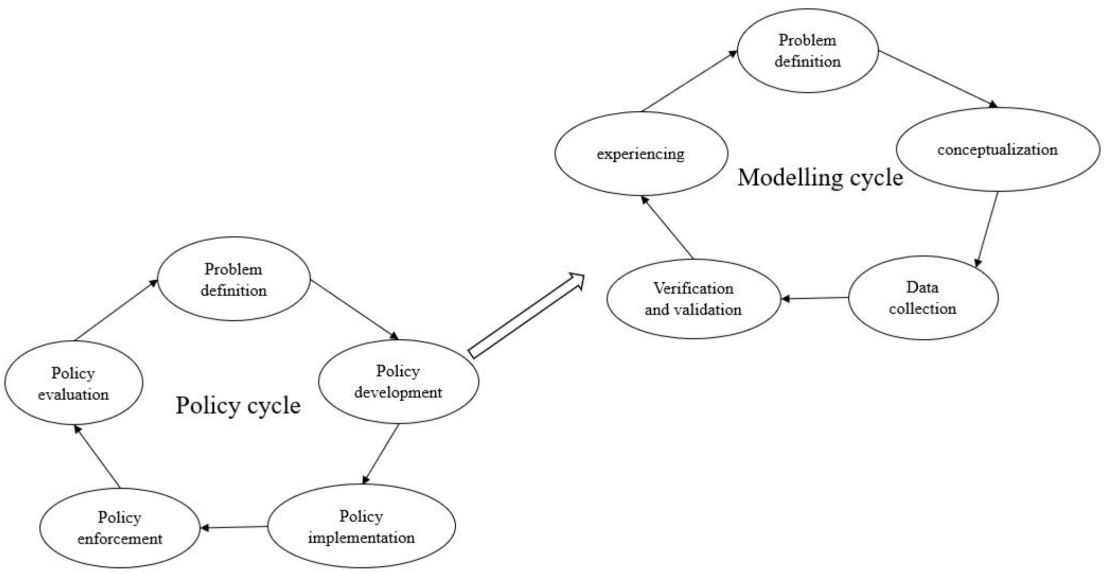


Figure 4.4 Policy Cycle and Modeling Cycle

4.6.3 Practical Implications

The study has implications for policymakers and social media operators in combating misinformation during exceptional crises, aiding in navigating infodemics effectively.

First, the findings indicate that increased user engagement would ensure a reduction in misinformation diffusion, suggesting the potential for social media users to discern misinformation. This is because greater involvement by rational individuals enhances the likelihood of truth prevailing and marginalizes misinformed messages. To enhancing user engagement, this study recommends employing both unilateral and bidirectional strategies. Presently, the unilateral approach, which prioritizes increasing message popularity among a broad audience, may not always succeed, given the limited capacity of the public to consume extensive government posts (Landi, Costantini, Fasan, & Bonazzi, 2021). And the bidirectional information flow approach, intended to enhance commitment in government-citizen dialogue, may not fully address individual concerns due to potential competency or resource limitations (Landi et al., 2021). Hence, a suggested improvement for the first approach is to enlist a political influencer as a local government representative. This can elevate the visibility of the local government's social media account by introducing an authentic and receptive figure who captures public attention. Consequently, it not only maintains message popularity but also spares citizens from having to deal with extensive government posts (Gaëlle, Sara, David, Liselot, & Charlotte, 2021; Ren, Dong, Popovic, Sabnis, & Nickerson, 2022). Moreover, to enhance the bidirectional approach, an offline community outreach program endorsed by knowledgeable specialists should be established, and online replies to citizens' posts should be proactively increased, both of which offer more supportive resources. These approaches can better facilitate citizens' comprehension of scientific information, address low commitment, enhance community trust in public administration, thereby mitigating misinformation spread.

Second, this study has explored the potential mechanisms underlying the impactful content factors (face coverings, international economic support, and screening methods) in countering misinformation diffusion. The adoption of protective behaviors serves as a buffering resource against misinformation diffusion (Allington, Duffy, Wessely, Dhavan, & Rubin, 2021). Confronted with uncertainties, people prefer to make decisions by assessing the value of potential options. In the research context, they are either engaging in protective behaviors or receiving medical treatment. Given the limited efficacy of early-stage treatments, people were more likely to adopt the former option, with face coverings being an obvious example. The execution of international economic support policies also incentivized more protective behaviors since people were better able to afford protective equipment financially (Li & Liu, 2020). Another underlying mechanism revolves around public trust (Laato et al., 2020). These economic policies fortified public trust by strengthening economic freedom (Shirish, Srivastava, & Chandra, 2021). Regarding the content topic of screening methods, the improper use of pandemic screening kits led to spurious comments on their reliability, weakening public trust (Patriquin et al., 2021). Yet, as testing expanded to a larger population, public trust grew, gradually dispelling misinformed messages (Karanasios, 2022). Accordingly, this study recommends both bolstering public trust and amplifying the volume of detailed descriptions of protective behaviors in online messages during public health crises. Besides, the findings on the inefficacy of content similarity suggest reducing its emphasis in misinformation control efforts. While its impact might be more noticeable in the dissemination of other general information, the discovery serves as a reminder to policymakers to adopt distinct strategies for combating misinformation (Feng et al., 2021).

Third, the research outcomes reveal a range of moderating influences wielded by government policies in molding misinformation diffusion. These influences depend on different levels of information richness rooted in attributes inherent in said policies (Zhou et al., 2021; Yin et al., 2018). Accordingly, this study suggests policymakers strategically incorporate these mechanisms into the improvement of two-way communication, ultimately mitigating misinformation diffusion. For instance, viewed as a stick policy, the vaccination policy is enforced with strong authoritarian oversight, as evidenced by its specialty and implementation controls (Bemelmans-Videc et al., 2017). Speciality control emerges from the inability of ordinary citizens to develop the COVID-19 vaccine, while implementation control is evident in the mandated vaccination requirement across multiple nations (Duch et al., 2021; Iguacel et al., 2022). Hence, these authoritarian controls curtail information richness, diminishing the effectiveness of vaccination policies in countering misinformation. this study recommends policymakers broaden communication channels, potentially through collaborations with reputable universities, healthcare institutions, and public organizations, to enhance public awareness and amplify specific topics' visibility. This, in turn, would enrich the information richness, leading to more robust outcomes in curtailing misinformation diffusion. Conversely, policies such as containment, economic measures, and health interventions, deemed as sermon policies, entail a higher degree of TWRC. To sustain and optimize their moderating efficacy, the implementation of these policies needs to be dynamically adapted to attain optimal objectives while operating within the constraints of diverse healthcare systems across societies (Ferguson et al., 2020). Thus, this study propose policymakers enrich the vertical depth of information flow by consistently promoting factual messages and linking them to fact-checking websites, distinguishing them from conspiracy-oriented online groups. These approaches would potentially foster scientific understanding, alleviate cognitive constraints in comprehending policy objectives, and ultimately reduce misinformation spread.

4.7 Limitations and Future Directions

This study has acknowledged certain limitations in the study, which can help guide future research in this important domain. First, the reliance on Twitter as the primary data source might have introduced bias into the findings given its limited representativeness for the entire population. Future researchers could enhance generalizability by conducting a comparative study incorporating data from other social media platforms. Second, this study did not address the proposition by Warner et al. (2022) that individuals tend to share misinformation if it aligns with their political ideology. Future researchers are thus encouraged to investigate the interplay between political ideology and people's perceptions of policy to comprehensively understand misinformation propagation. Third, considering the ongoing evolution of the internet, the dynamics of misinformation diffusion during crises can exhibit variability across cases. This study captures local government practices at a specific juncture. Subsequent investigations could expand upon this research by examining diverse crisis events, enlarging the study cohort, and encompassing various forms of public administration.

Chapter 5. The Impact of Misinformation on Government Policy Performance: Moderating Effects through Public Risk perception

5.1 Abstract

Influenced by subjective public risk perceptions, misinformation can either be magnified or minimized during transmission, thereby impacting the efficacy of government policies in managing crises. However, various risks perceived during crises remain relatively unexplored. Drawing on the Protection Motivation Theory, which considers diverse individual decision-making processes when confronted with risks, this study proposed a conceptual model to uncover the nuanced role of risk perception during a crisis. Using the COVID-19 pandemic as the case of this paper, hypotheses are tested using data collected on perceived risks at three different levels: overall (macro-level), interpersonal (meso-level), and individual (micro-level), covering the period from February 2020 to January 2022. Consequently, this study found a detrimental impact of misinformation diffusion on the effectiveness of government policies during the crisis. This deleterious impact could be further alleviated through heightened macro- and meso-level risk perceptions but exacerbated by an escalation in micro-level risk perception. The findings provide insightful discussion to elucidate the risk perception paradox: why individuals can be vulnerable to misinformation's impact on policy performance under specific circumstances yet exhibit resilience against its influence in other situations. Accordingly, this study advocates for policymakers and public health authorities to craft refined and targeted risk communication strategies by considering the heterogeneous nature of the public's risk perception.

Keywords: misinformation, government intervention policies, risk perception, crisis management, COVID-19.

5.2 Introduction

Misinformation, defined as false or misleading information that is spread intentionally or unintentionally, has emerged as one of the most critical factors affecting the performance of government policies in contemporary society, particularly during times of crisis (Wamsler et al., 2023). In an era characterised by rapid dissemination of information through various channels, including social media, misinformation possesses the potential to significantly shape the public perceptions and behaviours, ultimately influencing the effectiveness of governmental initiatives. The influence of misinformation on government policy implementation can arise from a multitude of complex factors, including distorted public perceptions, the intensity of proliferation of misinformation, and the erosion of trust () It has been revealed that misinformation can lead the general public astray, causing distorted adoption of government policies (Mulgan, 2007). For example, individuals might focus their attention on trivial matters that do not correspond to the actual challenges at hand (Clarke, 2016). This misallocation of efforts and resources can result in policy objectives not being achieved as intended. Further, false narratives and deceptive claims can sway public opinion, entrenching even more misconceptions about the intended goals and outcomes of the policies. This creates a situation in which genuinely effective policies may get dismissed due to the influence of misinformation, ultimately obstructing their potential for success. Having considered these consequences, the diffusion of misinformation could erode trust on proposed policy, as individuals might become increasingly sceptical of official statements. This scepticism weakens public willingness to cooperate with policies, resulting in reduced compliance and obstructing successful implementation (Newton, 2020). For instance, during the COVID-19 pandemic, the continuous exposure to misinformation resulted in decreased reliance on the medical guidance provided by the UK government, leaving people's faith in adhering to these directives notably compromised (Newton, 2020). Therefore, understanding how misinformation infiltrates people's decision-making processes and its subsequent ramifications is paramount for comprehending the intricacies of modern governance and its outcomes.

Past literature (such as, Dedeoğlu and Boğan (2021); Wachinger et al. (2013)) discovered that while disseminating various information, the role of how people perceive pre-existing risks associated with a given event has gradually emerged as influencing the performance of government policies. The perception of risk, which is defined as subjective and detached from material conditions, plays an important role in fuelling public compliance in government response policies to a perceived problem (Sledge & Thomas, 2021; Vieira et al., 2022). Within the research context, risk perception refers to the process through which individuals intuitively perceive the degree of risk or uncertainty associated with the hazard posed by a crisis such as COVID-19. When confronted with a crisis, heightened risk perception often leads to an uptick in risk mitigation behaviours, including a more steadfast adoption of governance measures. This, in turn, bolsters the effectiveness of policy implementation (Wachinger et al., 2013). Likewise, risk perception has been noted to exhibit a positive correlation with an index of preventative health behaviours that are in alignment with the overall objectives of policy implementation, consequently enhancing their implementation performance (Dryhurst et al., 2022). More notably, for misinformation diffusion, it's crucial to recognise that the influence of risk perception could lead to the exaggeration or downplaying of misinformation during transmission, thereby imposing different effects on the execution of government management policies (Ho et al., 2022; Larson et al., 2022). Therefore, there is a pressing need for greater clarity concerning the extent of its role as an intermediary element in shaping government policies, particularly in the presence of prevailing misinformation.

However, current scholarly investigations into this potential intervening mechanism have not sufficiently explored the crucial role of risk perception, especially in context of intensity of misinformation diffusion. It has been argued that risk perception operates as a filtering mechanism through which individuals evaluate the potential consequences tied to specific information, consequently influencing ensuing responsive behaviours (Dedeoğlu & Boğan, 2021; Kasperson et al., 2022). To further substantiate this perspective, Gerber and Neeley (2005) provide more compelling evidence for the dynamics of public policymaking and risk perception. It is revealed that citizens' attitudinal factors in processing policy-related information, coupled with an elevated sense of risk perception, significantly contribute to enhancing the degree of endorsement towards government intervention measures of addressing potential hazards (Sledge & Thomas, 2021). This observation suggests a potential role of risk perception in shaping citizens' interpretations and responses to misinformation, thereby emphasizing the necessity of investigating its impact on the efficacy of policies. Additionally, the ongoing investigation of risk perceptions has not fully disentangled the nuanced dimensions of this concept (Qiao et al., 2023). As posited by Yates (1992), risk inherently assumes a subjective nature, embodying the interplay between the event and the risk taker (Vieira et al., 2022). This intrinsic subjectivity has led to the absence of a uniform measure of risk perception that can be applied across different hazards and disciplines (Vieira et al., 2022; Wilson et al., 2019). Therefore, the examination of risk perceptions demands a finer granularity. It becomes essential to integrate more precise risk perceptions into the investigation of public messages, especially within the domain of government policy management (Qiao et al., 2023). Thus, the approach adopted a granular measurement to examine risk perceptions at three different levels: overall (macro-level), interpersonal (meso-level), and individual (micro-level).

To bridge these gaps, this study examined the influence of misinformation diffusion on policy performance during a crisis and explored the potential impact of risk perception at different levels of granularity on this relationship. the study was guided by the Protection Motivation Theory (PMT) as a theoretical lens, providing insights into the diverse processes of individual decision-making when facing risks. To substantiate the idea, this study selected the COVID-19 pandemic as the case of the study and employed a text-search methodology to test hypotheses on data extracted from online platforms, spanning from February 2020 to January 2022. Ultimately, this study unveiled a detrimental impact of misinformation diffusion on the effectiveness of government policies during crises. Additionally, this detrimental impact could be alleviated through heightened macro- and meso-level risk perceptions but exacerbated by an escalation in micro-level risk perception, influencing the effectiveness of government policies in varying ways. The findings of this study have both theoretical and practical implications. Theoretically, the novel application of PMT by incorporating a granular interpretation of citizens' risk perception in the context of crisis has enhanced a more potent avenue for mutual communication, contributing to building effective risk-communication strategies (Kellens et al., 2013). Moreover, the research has advanced the existing literature (Kahneman & Tversky, 2013; Tversky & Kahneman, 1992) by providing valuable insights to elucidate the risk perception paradox, which examines why individuals can be susceptible to misinformation's effect on policy implementation under certain conditions while demonstrating resilience against its influence in other situations (Wachinger et al., 2013). Furthermore, the investigation of misinformation intertwined with risks within the realm of government policy management has the potential to facilitate the cultivation of a more robust and all-encompassing risk governance model (Renn et al., 2011). Regarding practical implications, a knowledge repository containing potential misinformed topics concerning government policies is suggested to be integrated with public management systems. This collaboration has the potential to iteratively reduce the likelihood of misinformation, enhancing the probability of successful policy execution (Alhawari et al., 2012). In addition, the findings on the diverse moderating role of risk perception have advocated for policymakers and public health authorities to formulate more nuanced and focused risk communication strategies which entails taking into account the heterogeneous nature of the public's risk perception (Kellens et al., 2013). Lastly, this study proposes that policymakers embrace various online media platforms in collaborative problem-solving processes to analyse misinformation issue, therefore enhancing policy efficacy in crisis management efforts (Guo et al., 2021; Park et al., 2015).

5.3 Theoretical Background and Hypotheses Development

5.3.1 Theoretical Background

PMT was originally developed to explain factors that can motivate people to change their health-related behaviours to protect themselves (Rogers, 1975). Its primary objective is to persuade people to follow communicator's recommendations (Floyd et al., 2000; Yoo et al., 2021). In recent times, this theory has experienced a resurgence in the domain of information diffusion and public policy management due to its robust explanatory capabilities. Researchers have employed PMT to identify variables influencing decisions related to risk and assess its efficacy in predicting protective actions (Herath & Rao, 2009; Yoo et al., 2021).

According to PMT, the decision of individuals to engage in a protective or nonprotective response when faced with a risk or uncertainty is driven by two main cognitive processes, namely, *threat appraisal* and *coping appraisal* (Bubeck et al., 2018; Rogers et al., 1997). *Threat appraisal* refers to the assessment of the severity associated with a particular risk and perceived probability of its occurrence (Bubeck et al., 2018). In other words, threat appraisal focuses on the evaluation of the risk itself. If the perceived risk is high, individuals are more likely to feel motivated to engage in protective behaviours. In the context of pandemic crisis, where misinformation can be prevalent, if people perceive surrounding risks to be high, they are more likely to be cautious and seek accurate information from reliable sources, leading to well-received pandemic management policies and a positive impact on policy performance. *Coping appraisal*, on the other hand, involves the evaluation of one's perceived ability to successfully carry out the necessary protective behaviours to mitigate the identified risks or uncertainty (Yoo et al., 2021). It encompasses the assessment of one's self-efficacy (confidence in one's ability to perform the protective actions) and response efficacy (belief in the effectiveness of the recommended protective measures). In other words, coping appraisal focuses on the evaluation of one's own capabilities and the available resources to deal with the risk. In particular, two types of coping responses exist, namely, adaptive and maladaptive responses (Rippetoe & Rogers, 1987). Adaptive responses can help reducing potential risks, whereas maladaptive responses contribute to an increase in perceived risks. These coping responses guide individuals' decisions on how to react to recommended protective measures (Yoo et al., 2021). In the context of crises characterized by the pervasive nature of misinformation, the impact of these coping responses, which already exhibit variations, may be further escalated (Yoo et al., 2021). Given the diverse characteristics of misinformed message recipients, both types are worthwhile to be discussed, thereby assisting policymakers in discovering suitable management skills and addressing the challenges posed by misinformation in certain situations (Wang et al., 2017; Yoo et al., 2021). Overall, the interplay of threat and coping appraisal influences protection motivation, which is considered as an intervening variable that arouses, sustains, and directs the activity of individuals to protect the self from danger (Bubeck et al., 2018).

5.3.2 Hypotheses Development

5.3.2.1 Misinformation Diffusion and Government Policy Performance

Misinformation refers to false or inaccurate claims that act as an umbrella term for interchangeable words and expressions such as conspiracy theories, false rumours, fake news, propaganda and disinformation (Wu et al., 2019). It has become particularly pronounced in the context of public health outbreaks, as the diffusion of misinformation can have far-reaching consequences beyond those directly exposed, potentially impacting the broader population (Bursztyn et al., 2020; Islam et al., 2023). The abundance of misinformation circulating among the public has the potential to engender misinterpretations or distortions of government policies aimed at managing the crisis. Consequently, this induces confusion, subsequently triggers misinformed behaviours, and ultimately paralyses the effectiveness of government policies. Thus, understanding misinformation diffusion is imperative when crises unfold in order to assess the overall performance of government policies (Islam et al., 2023).

By distorting public's perception of policies, misinformation could manifest in behaviours such as the disregard of recommended preventive measures or the misunderstanding of the necessity of certain guidelines, undermining the intended effectiveness of government policies (Robinson et al., 2021). For example, when individuals are misinformed about government policies regarding restrictions on group gatherings during the pandemic, there is a possibility that they engage in non-essential outings, thereby increasing their susceptibility to viral infections and compromising the effectiveness of the policy in question (Benke et al., 2020). Likewise, misinformed messages discrediting health protective measures, such as mask-wearing's effectiveness in avoiding infection, may lead individuals to perceive them as illogical and not to comply (Islam et al., 2023). Moreover, the unsubstantiated claims surrounding the safety, ingredients, or efficacy of newly invented vaccines have emerged as a major apprehension in the implementation of vaccination policies during the pandemic, since it would potentially amplify vaccine hesitancy, impede vaccine acceptance rates, and ultimately reduce the likelihood of achieving heightened levels of immunity within populations (Suarez-Lledo & Alvarez-Galvez, 2021; Truong et al., 2022). Furthermore, to comprehensively address the well-being of citizens experiencing the pandemic, economic policies have been adopted to ensure the affordability of essential life and hygiene necessities, crucial for self-protection. However, it has been observed that the uncertain information surrounding these policies could misguide individuals in their spending practises, possibly leading to budget constraints when it comes to acquiring protective equipment for effectively safeguarding against the virus (Aljanabi, 2023).

Recognising these, emerging research findings have also noted potential contributors to the adverse effects of misinformation diffusion on government policy performance. Empirical evidence suggests that individuals tend to perceive information as reliable, even if it is misleading, when it aligns with broader societal acceptability, especially within their social networks (Islam et al., 2023; Lewandowsky et al., 2012). Consequently, the public could be susceptible to accepting misleading arguments and subsequently engaging in misinformed behaviours. For instance, since this heightened acceptability would impact individuals' ideology and beliefs, they are less likely to perceive factually accurate information as reliable if it contradicts their pre-existing misinformed beliefs (Lewandowsky et al., 2012). Accordingly, misinformation can give rise to cognitive biases that violate the intended objectives of government policies. In addition to pre-existing beliefs, newly acquired knowledge concerning government management policies can also be subject to the diffusion of misinformation. According to Bose (2004)'s work, knowledge acquisition is influenced by contextualised information. So, during a crisis riddled with widespread misinformation, individuals may inadvertently acquire knowledge rooted in misinformed statements regarding government policies. This can further amplify misunderstandings about these policies, impeding comprehension of the genuine motives behind government decisions and ultimately undermining the intended positive impact of these policies (Michelle Driedger et al., 2021; Vinck et al., 2019). Given these factors, the two-way communication channel between governments and citizens may be disrupted, inhibiting the transmission of accurate information to the public and eventually jeopardising the efficacy of government policies (Mansoor, 2021). Therefore, this study hypothesizes that:

H1. Misinformation diffusion has a negative impact on the performance of government policy of managing the COVID-19.

5.3.2.2 The Moderation Effect of Risk Perception

Risk perception is an information-based construct characterised by a lack of consensus on its definition and measurement, making it more pragmatic than firmly grounded in theoretical underpinnings (Leppin & Aro, 2009; Vieira et al., 2022). In the research context, risk perception refers to the process through which individuals intuitively perceive the degree of risk or uncertainty associated with the hazard posed by a pandemic such as COVID-19. Empirical evidence has consistently revealed the significant role of risk perception in fuelling public interest in government policy to respond to a certain problem (Robinson et al., 2013; Sledge & Thomas, 2021). Therefore, intensive discussions concerning information related to government policies may engender diverse public responses and ultimately varying levels of policy effectiveness, influenced by risks perceived at various levels such as overall (macro-level), interpersonal (meso-level), and individual (micro-level).

Risk perception acts as a filter through which individuals evaluate the potential consequences associated with specific information, thereby influencing subsequent responsive behaviours (Dedeoğlu & Boğan, 2021). For instance, encountering inaccurate and unreliable information concerning government crisis management policies, individuals may, influenced by their perception of multiple risks emanating from the immediate environment, hesitate to adhere to these guidelines, ultimately contributing to uncertain outcomes in policy implementation. This highlights the pivotal role of risk perception in shaping the overall effectiveness of government policies when addressing a crisis plagued by widespread misinformation. It has been revealed that trust in government-related information may exist behind the scenes, explaining the moderation effect of risk perception. Trust is typically developed through interactions within trust-based relationships, implying that individuals who have established a trust-based relationship with a particular group tend to believe the information conveyed by that group irrespective of its specific content (Islam et al., 2023). Given the widespread occurrence of false and ambiguous information during the COVID-19 pandemic, trust could vacillate in how people perceived potential risks from different external channels, causing misinformation to be either further exaggerated or downplayed and ultimately impacting the effectiveness of policy implementation (Ho et al., 2022; Islam et al., 2023). Thus, diverse levels of risk perception would result in varying degrees of individual preparedness, subsequently influencing risk mitigation behaviours in distinct ways (Wachinger et al., 2013).

To be more specific, this experience of trust-forming relationships has served as a significant milestone in fostering a sense of willingness to act and preparedness for crisis events, potentially resulting in the emergence of varying moderation effects of risk perception on government policy performance (Wachinger et al., 2013). When people possess a high level of trust in management's ability to handle crises, it leads to a decrease in their personal perception of risk, triggering more risk-seeking behaviours by exploring alternative solutions based on the misinformation they are exposed to (Bubeck et al., 2018). Trust here lessens the perception of adverse consequences in terms of both likelihood and magnitude, consequently reducing individuals' inclination towards preparedness actions. As a result, this exacerbates the detrimental effects of misinformation on government policy performance. Conversely, their negative relationship can be mitigated through the adoption of more risk-avoiding behaviours. Therefore, this study proposes that:

H2. Risk perception can moderate the relationship between misinformation diffusion and the performance of government policy of managing the COVID-19.

The aforementioned explanation strongly indicates that individuals' perception of risk is actually contingent upon their subjective interpretation of the provided information (Islam et al., 2023; Paton et al., 2008). Individuals can determine which risks are deemed to be important and the nature of the signals that this crisis portends (Vieira et al., 2022). In this context, it is necessary to delve deeper into a more comprehensive delineation of risk perceptions to enhance the understanding of the complex dynamics between misinformation diffusion, risk perception, and government policy performance.

Accordingly, risk perceptions can be categorised at macro-, meso-, and micro-level (Inouye, 2014). Macro-level risk perception refers to risks that transcend individual impacts and can potentially pose substantial disruptions on a broader scale, affecting entire society, including factors such as economic recessions, climate change, geopolitical conflicts, and factors influencing overall global stability. Meso-level risk perception refers to the significant influence exerted by peers or community on how individuals perceive risks. This influence can lead individuals to take risks that contradict their own better judgement, highlighting the impact of peer influence on risk-taking behaviours (Davey et al., 2008; Inouye, 2014). Micro-level risk perception refers to individual knowledge of a situation and the presence of an optimism bias, where individuals tend to believe they are less likely to experience negative events (Inouye, 2014). More specifically, this study posits that when confronted with macro- and meso-level risks during crises, individuals may perceive their ability to mitigate these risks as insufficient, given the broader impact and complicated interpersonal relations. For example, people may encounter geopolitical risks through news media reports highlighting intensive relations between two countries, potentially disrupting the supply chain. This poses a significant risk to the affected population, obviously exceeding their capacity for effective management. Similarly, when engaging in online discussions about event cancellations, people face risks beyond their ability to influence outcomes or verify the accuracy of information regarding the cancellations. Consequently, they tend to rely on government guidelines to avoid such risks, thus mitigating the adverse impact of misinformation diffusion on policy performance. On the other hand, individuals tend to perceive their ability to mitigate micro-level risks more efficiently, as it is more feasible compared to addressing macro- and meso-level risks. For instance, individuals often search for information online and interpret it independently. During the pandemic, with housing prices increasing, someone might evaluate their financial status and determine they have adequate savings to address this risk, prompting them to increase their investment in property. So, this could further lead to risk-seeking behaviours driven by the belief that these risks are manageable through their perceived abilities (Ewart, 1991; Hirschi, 2015). As a result, this behaviour can contradict government policy guidelines, thereby amplifying the negative impact of misinformation diffusion on government policy performance. Accordingly, this study proposes that:

H2.a When macro-level risk perception is high, there is a reduced likelihood of misinformation diffusion having a negative impact on the performance of government policy of managing the COVID-19.

H2.b When meso-level risk perception is high, there is a reduced likelihood of misinformation diffusion having a negative impact on the performance of government policy of managing the COVID-19.

H2.c When micro-level risk perception is high, there is an increased likelihood of misinformation diffusion having a negative impact on the performance of government policy of managing the COVID-19.

The conceptual model depicting the relationships among different variables is shown in Figure 5.1.

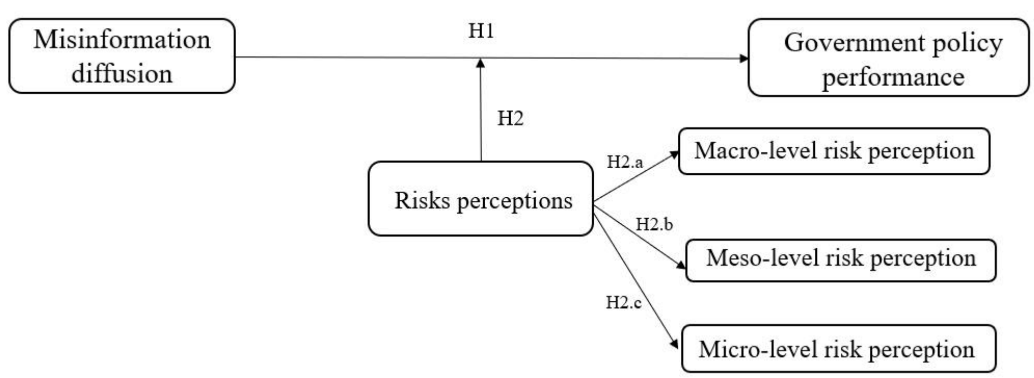


Figure 5.1 Conceptual Model

5.4 Methodology

5.4.1 Data Collection and Preprocessing

Various pandemic management policies, as tracked by the Oxford Covid-19 Government Response Tracker (OxCGRT) project (Hale et al., 2020), were posted publicly. It can be broadly classified into four categories: containment, economics, health and vaccination. This project also includes a list of keywords related to each policy, which helped us collect relevant tweets (as shown in Table 5.1). this study then used the Twitter (now called 'X') Application Programming Interface (API) to extract 1.2 million tweets from February 2020 to January 2022 that discussed these policies. Geolocations, follower counts, like counts, comment counts, retweet counts and hashtags were also collected for these policies.

Since the study specifically focused on the UK, further filtering was required. This was accomplished by retrieving valid country names using the 'pycountry' package (pycountry, 2022) and mapping city names to source nations with the aid of world city data (DataHub, 2018). Cities that could be matched to multiple countries were assigned to the country with the largest population, as this study assumed that people from the largest city would be more likely to omit country identifiers (Chum et al., 2021). This approach raised the availability rate of raw geolocation data from 18.7% to 61% and allowed for the collection of a cleaned dataset of 144K tweets from February 2020 to January 2022 in the UK. Finally, this study kept English-only tweets; converted the text to lowercase; removed HTML tags, @usernames, numbers, punctuation marks, special characters and stop words; and tokenised the content.

Table 5.1 Government Policy Keywords

Government Policies	Keywords
Containment	school closure, work from home, cancel event, gathering ban, transport ban, stay at home, travel ban
Economic	income support, debt relief, economic stimulus, international support
Health	health campaign, PCR, contact tracing, health investment, face mask, protect elderly
Vaccination	vaccine priority, vaccine available, vaccine investment

5.4.2 Measures

5.4.2.1 Dependent Variables

The performance of government policies 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. this study employed the Python epyestim package to estimate the reproduction number as

$$R_t = \frac{E[I_t]}{\sum_{s=1}^{t} I_{t-s} w_s}, \tag{5.1}$$

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).

5.4.2.2 Independent Variable

Misinformation diffusion is generally measured by Twitter's unique retweeting feature, which is a powerful mechanism for information sharing (Stieglitz & Dang-Xuan, 2013). Misinformed tweets originating from the previously acquired corpus of tweets regarding government policies for managing the pandemic are identified to measure misinformation diffusion. Specifically, the COVID-19 Fake News Detection dataset was used to create a classification model for this purpose; this is exemplified in Appendix 3. This class-wise balanced dataset has found extensive utilization within the realm of information systems research (Chriqui & Yahav, 2022; Huang & Wei, 2022). It comprises Twitter posts that are manually annotated and fact-checked, pertaining to discussions surrounding the COVID-19 pandemic (Patwa et al., 2021). This corpus lie tweets deemed to be misinformed, as per the defined criteria for misinformation. In the dataset, 3,360 tweets were labelled as non-misinformation, and 3,060 tweets were labelled as misinformation. Before the final classification, the model selection was performed, including the three most suitable classifiers: Logistic Regression, Naive Bayes, and Support Vector Machines. They utilized 80% of the overall dataset for training and the remaining 20% for validation, with their evaluation metrics detailed in Appendix 3. Finally, the best set of precision, recall and F-1 scores were obtained from a logistic regression classifier; these were 92%, 97% and 94%, respectively. this study applied this model to classify the unlabelled tweets. The diffusion of misinformation was measured by the daily percentage of retweets of misinformed posts.

Risk perception is categorised into macro-level, meso-level, and micro-levels, based on the scope and scale of the factors influencing it (Inouye, 2014). To accurately assess these levels, this study employs a text-based measure to extract risk perceptions derived from news media, social media, and search engine sources. This approach enables a comprehensive assessment of risk perception across different levels.

First, *macro-level risk perception* is derived from the work of Baker et al. (2016), who have developed a set of indices serving as proxies for risks and uncertainties stemming from overarching regulatory frameworks. These risks may originate from various regions across the globe. The measurement relies on an extensive automated text-search of news media coverage, incorporating human readings of 12,000 newspaper articles, enhancing its reliability and generalizability (Baker et al., 2016). Grounded in these articles, the indices are calculated based on the frequency count of the terms "risk" or "uncertainty" (and their variants), as well as keywords describing various dimensions of global dynamics in the same set of newspaper (Aljanabi, 2023; Baker et al., 2016). Subsequently, macro-level risk perception is converted to a daily scale and encompasses factors influencing global dynamics from multiple perspectives, including the economy, climate, geopolitics, and overall global stability. Table 5.2 provides additional details on the sourcing of news media coverage.

Table 5.2 Macro-level Risk Perceptions

Macro-level risk perception	News media coverage	Keywords
Economy	Eleven UK newspapers: The FT, The Times and Sunday Times, The Telegraph, The Daily Mail, The Daily Express, The Guardian, The Mirror, The Northern Echo, The Evening Standard, and The Sun.	economic, economy, business, commerce, industry, industrial, tax, policy, regulation, spending, deficit, budget, Bank of England, war, tariff
Climate	Eight leading US newspapers: Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today and the Wall Street Journal.	climate, climate risk, carbon dioxide, greenhouse gas emissions, CO2, carbon dioxide, global warming, climate change, green energy, renewable energy, environmental, environment
Geopolitics	Ten leading US and UK newspapers related to adverse geopolitical events: Chicago Tribune, the Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, the Los Angeles Times, The New York Times, USA Today, The Wall Street Journal.	war threats, peace threats, military build-ups, nuclear threats, terror threats, beginning of war, escalation of war, terror acts
Overall global stability	The Economist Intelligence Unit (EIU) country reports offer a comprehensive examination of various factors and their impact on the global landscape.	These reports delve into multiple dimensions, including politics, economy, regulations, business, industries, environment, and more.

Second, *meso-level risk perception* primarily delineates risks perceived through interactions within group discussions on social media platforms. Its measurement crucially relies on the combination of two broad and comprehensive lexicons specifically focusing on the seed words of "risk" and "uncertainty", as pioneered by Hassan et al. (2019); Kent (1964); Wu (2023). Hassan et al. (2019) built upon the latest firmly established research on leveraging machine learning-based techniques to develop a lexicon encompassing a comprehensive collection of synonyms for the core term "risk" (Jegadeesh & Wu, 2013; Loughran & McDonald, 2011). This lexicon has gained widespread adoption among researchers in the business domain (Caldara et al., 2020; Campbell et al., 2014). Another lexicon is derived from Kent (1964)'s chart. Widely acknowledged as the pioneer of intelligence analysis, Kent (1964) made substantial contributions to the comprehension of how individuals can be misled by ambiguous expressions of uncertainty and compiled a collection of expressions denoting the core term "uncertainty". This chart has been extensively employed in the field of risk management, serving as a valuable tool for practitioners in assessing and managing uncertainties effectively (Auger & Roy, 2008; Duijm, 2015; Weiss, 2008). As such, these two lexicons synergistically complement each other, effectively bolstering the precision and applicability of the construction of the meso-level risk perception measure. Table 5.3 provides additional details pertaining to the lexicons. Consistent with the most dominant methodology in text analysis – the bag-of-words (BoW), the rationale behind the measurement is that individuals facing increased levels of risk are prone to participate in more discussions about these risks on social media platforms like Twitter (Wu, 2023). On this basis, a greater proportion of risk-related keywords are conveyed, further reinforcing the necessity of employing lexicons to facilitate an effective measurement. This methodology quantifies the daily amount of discussion on a given topic by tabulating the frequency of keywords describing that topic. Besides, Twitter has been selected to assess risk perception at the meso-level due to its fundamental attribute of enabling communication and interaction among peers, in line with the definition of the meso-level (Utz et al., 2013).

Table 5.3 Meso-level Risk Perception Lexicon

Source	Keywords
Hassan et al. (2019)'s risk-related words	risk, jeopardize, riskiness, risks, unsettled, treacherous, uncertainty, unpredictability, oscillating, variable, dilemma, perilous, chance, skepticism, tentativeness, possibility, hesitancy, unreliability, pending, riskier, wariness, uncertainties, unresolved, vagueness, uncertain, unsure, dodgy, doubt, irregular, equivocation, prospect, jeopardy, indecisive, bet, suspicion, chancy, variability, risking, menace, exposed, peril, qualm, likelihood, hesitating, vacillating, threat, risked, gnarly, probability, unreliable, disquiet, unknown, unsafe, ambivalence, varying, hazy, imperil, unclear, apprehension, vacillation, unpredictable, unforeseeable, incalculable, speculative, halting, untrustworthy, fear, wager, equivocating, reservation, torn, diffident, hesitant, precarious, fickleness, gamble, undetermined, misgiving, risky, insecurity, changeability, instability, debatable, undependable, doubtful, undecided, incertitude, hazard, dicey, fitful, tricky, indecision, parlous, sticky, wavering, unconfident, dangerous, iffy, defenseless, tentative, faltering, unsureness, hazardous, endanger, fluctuant, queries, quandary, niggle, danger, insecure, diffidence, fluctuating, changeable, precariousness, unstable, riskiest, doubtfulness, vague, hairy, erratic, ambivalent, query, dubious
Kent (1964)'s chart for expressions of uncertainty	believe, evident, doubt, highly, likely, almost, certain, should, probable, fairly, expected, assume, appear, reasonable, logical, unlikely, doubtful, estimate

Third, *micro-level risk perception* mainly describes risks discerned through individual online searches. Using the Google Insights for Search (GIFS) Methodology, it is measured by individuals' Google searches in the UK for keywords that reflect concerns about risk in their immediate environment (GIFS, 2023). Typically, the initial stage of an individual's decision-making process involves a search for information (Sirakaya & Woodside, 2005). As the most extensively utilised online search engine, Google provides real-time insights through its query data, capturing the awareness of individuals equipped with the requisite devices and services to perform web searches (Muchow & Amuedo-Dorantes, 2020; StatCounter, 2023).

It has served as a valuable, user-friendly, widely accessible, and cost-effective tool to assess individual perceptions regarding specific topics, thereby positioning individuals' minds on a certain subject (Muchow & Amuedo-Dorantes, 2020; Reyes et al., 2018). Therefore, in accordance with the methodologies utilised in previous established research in information management and social media analysis, this study adopt the GIFS to identify the dynamic patterns displayed by individuals in their search queries pertaining to risk perceptions amid the COVID-19 pandemic (Kwak et al., 2010; Vosen & Schmidt, 2011). Furthermore, keywords associated to social determinants of health (SDOH) are applied into the extraction of micro-level risk perception from Google searches. These keywords are justified since they are defined as contextual factors that contribute to increased individual risk of exposure to disease or compromise the ability to protect against infections, which align with the research context (Qiao et al., 2023). Specifically, rooted in Göran and Whitehead (1991)'s model of SDOH, as emphasised on the GOV.UK website for introducing social determinants of health, this study has compiled an inclusive list of SDOH keywords, effectively depicting various aspects of general living and working conditions (GOV.UK, 2023). These keywords are derived from the well-regarded WHO (2023) Conceptual SDOH framework and the HealthyPeople2030 (2023) project, both of which have been extensively applied within the realm of social science research (Nagata et al., 2013; Organization, 2021; Solar & Irwin, 2010). Table 5.4 provides a detailed exploration of these keywords, covering seven key dimensions. Accordingly, all these keywords, including the term "risk", are incorporated into search queries while conducting the GIFS, which has been quantified on a daily scale, facilitating a granular analysis of their temporal variations.

Table 5.4 SDOH Keywords

Domains	Dimensions	Search items
Living	Agriculture and food protection	Access to food, grocery store, convenience store, farmers market, fast food
	Education	Health literacy, institutional resource, educational attainment, educational level, graduate school, high school
	Work environment	safe working environment, job security, control over working patterns, challenging work, sense of belonging and meaningfulness, work engagement, social isolation, reward at work, stress-related disorders (Marmot, 2013).
Working	Unemployment	Employment, unemployment rate
	Water and sanitation	Water quality, air quality, pollution, greenspace, respiratory hazard index, sanitation, natural amenity index
	Health care services	Insurance type, insurance status, health coverage, payer type, primary care provider
	Housing	Living situation, housing conditions, living alone, cohabitation, multifamily residences, group home, home ownership, housing price

5.4.2.3 Control Variables

Two types of control variables are considered which have the potential to exert influence on the diffusion of misinformation: misinformation-related counts and the government response index. Specifically, misinformation-related counts include the number of replies, likes, and shares received by misinformed messages. Variations in these numbers would impact the diffusion of misinformation, thereby affecting policy implementation. The government response index reflects the comprehensive strictness exhibited by government policies in managing the pandemic, including containment, economic, health, and vaccination policies (Hale et al., 2020).

5.5 Findings

5.5.1 Descriptive Analysis

We performed descriptive statistics and Pearson correlation analysis of the variables included in the model, as shown in Tables 5.5 and 5.6. To investigate potential multicollinearity, the variance inflation factor (VIF) of each variable was inspected; the largest VIF was 8.8, which is below the threshold value of 10 (Aiken et al., 1991), indicating that multicollinearity did not influence the results of the study.

Table 5.5 Descriptive Statistics

	Variables	**Mean**	**Std. Dev.**	**Min**	**Max**	**VIF**
Control variables						
1	Reply count	183.28	332.23	0	6887	1.57
2	Share count	419.57	940.29	0	11437	4.30
3	Like count	1766.40	4145.05	0	54811	4.06
4	Government response index	63.04	13.75	8.33	83.96	1.34
Independent variables						
5	The diffusion of misinformation	0.49	0.25	0	1	4.66
6	Meso-level risk perception	0.20	0.07	0	1	6.76
7	Micro-level risk perception	19.74	2.61	14.02	30.48	8.80
8	Macro-level risk perception (economy)	395.27	257.63	63.11	548.05	3.96
9	Macro-level risk perception (climate)	7.24	2.41	3.17	13.71	7.92
10	Macro-level risk perception (geopolitics)	50.64	36.08	0	179.20	2.78
11	Macro-level risk perception (overall global stability)	0.63	0.28	0.27	1.45	4.79
Dependent variable						
12	Government policy performance	1.1	0.41	0.56	4.66	4.41

Note: Std.Dev: Standard deviation.

Table 5.6 Correlation Matrix

	Variables	1	2	3	4	5	6	7	8
1	Government policy performance	1							
2	The diffusion of misinformation	0.074**	1						
3	Meso-level risk perception	0.09**	-0.092**	1					

4	Micro-level risk perception	0.192***	0.189**	-0.234***	1				
5	Macro-level risk perception (economy)	0.185***	-0.09**	0.319***	-0.383***	1			
6	Macro-level risk perception (climate)	-0.058	-0.025	-0.023	-0.087**	-0.046	1		
7	macro-level risk perception (geopolitics)	-0.015	0.028	-0.04	0.014	-0.14***	-0.078**	1	
8	macro-level risk perception (overall global stability)	0.549***	0.129***	-0.095**	0.441***	-0.04	0.026	-0.056	1

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

5.5.2 Regression Analysis

We included interactive product terms as predictor variables to test the moderating effects of all risk perceptions. Ordinary least squares (OLS) regression model was employed to estimate the relationship between the independent variables and the government policy performance, with the results shown in Table 5.7. Model 1 only includes control variables; Model 2 includes the diffusion of misinformation; Model 3 includes meso-level risk perception; Model 4 includes micro-level risk perception; and Model 5 includes all variables. Figure 5.2 demonstrates the robustness of the models by illustrating that residuals can be represented by a normal distribution curve: (a) Histogram of residuals of Model 5; (b) P-P curve of residuals.

In Model 2, the coefficient associated with misinformation diffusion exhibits statistical significance, thereby supporting H1. This suggests that an escalation in the diffusion of misinformation leads to a corresponding rise in the reproduction number, signifying a decline in the effectiveness of government policies for managing the pandemic crisis. This discovery substantiates the assertion that the diffusion of misinformation yields a negative impact on government policy performance. The proliferation of misinformation could significantly increase likelihood of the public being influenced by distortions of government policies and engaging in misled behaviours, ultimately paralysing the performance of government policies. This finding reaffirms the argument presented by prior literature that pointed out the negative relationship between misinformation diffusion and government policy performance (Islam et al., 2023; Karanasios, 2022; Lewandowsky et al., 2012). According to Model 3, meso-level risk perception serves as a negative moderator in the relationship between misinformation diffusion and government policy performance, confirming H2.b. Specifically, as meso-level risk perception increases, the negative impact of misinformation diffusion on government policy performance is reduced. Model 4 presents a significant and positive coefficient of the interactive product terms between micro-level risk perception and misinformation diffusion, signifying that micro-level risk perception positively influences the original relationship between misinformation diffusion and government policy performance. This finding suggests that the incorporation of micro-level risk perception amplifies the adverse consequences of misinformation diffusion on government policy performance, thereby further diminishing its efficacy. Thus, H2.c is verified. In Model 5, it is discovered that macro-level risk perception acts as a moderator in the relationship between misinformation diffusion and government policy performance. The significant negative coefficients of the interaction terms indicate that macro-level risk perception enhances the strength of the negative association between misinformation diffusion and government policy performance, thereby supporting H2.a.

Table 5.7 Regression Results

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**

constant	2.1235***	2.0298***	1.9581***	1.8751***	1.1705***
	(0.0543)	(0.0596)	(0.0678)	(0.0808)	(0.1071)
Control variables					
Reply count	-0.0001***	-0.0001***	-0.0001**	-0.0001**	-0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Share count	0.0001	0.0000	0.0000**	0.0000**	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Like count	-0.0000**	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Government response index	-0.0159***	-0.0156***	-0.0152***	-0.0157***	-0.0080***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0010)
Independent variables					
MISINFO		0.1579***	0.1544***	0.1400***	0.0694**
		(0.0432)	(0.0426)	(0.0422)	(0.0370)
ME_RP			0.6451***	1.2180***	1.4689***
			(0.2030)	(0.2392)	(0.2301)
MI_RP				0.0000	0.0015**
				(0.0009)	(0.0008)
MA_RP_E					0.0005***
					(0.0001)
MA_RP_C					0.0332***
					(0.0079)
MA_RP_G					0.0019***
					(0.0005)
MA_RP_O					0.9817***
					(0.0675)
MISINFO*ME_RP			-0.0043***	-0.0090***	-0.0120***
			(0.0009)	(0.0014)	(0.0016)
MISINFO*MI_RP				0.0001***	0.0006**
				(0.0000)	(0.0000)
MISINFO*MA_RP_E					-0.0000***
					(0.0000)
MISINFO*MA_RP_C					-0.0003***
					(0.0001)
MISINFO*MA_RP_G					-0.0000***
					(0.0000)
MISINFO*MA_RP_O					-0.0049***
					(0.0005)
R^2	0.35	0.36	0.39	0.40	0.56
F	94.89***	79.92***	62.60***	52.06***	52.23***

Note: MISINFO: the diffusion of misinformation, MA_RP_E: macro-level risk perception (economy), MA_RP_C: macro-level risk perception (climate), MA_RP_G: macro-level risk perception (geopolitics), MA_RP_O: macro-level risk perception (overall global stability), ME_RP: meso-level risk perception, MI_RP: micro-level risk perception. Standard errors are reported in parentheses.

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

5.5.3 Robustness Checks

Lastly, this study performed several robustness checks to assess the quality and validity of the analysis. First, the addition of all the independent variables in Model 5 has led to a notable improvement in the model's fit, as evidenced by the increase in the fitting degree (R^2), thereby substantiating the validity of the proposed model. Furthermore, Figure 5.2 depicts the distribution of residuals. Specifically, (a) the histogram of residuals in Model 5 showcases a distribution that aligns with a normal curve, indicating a satisfactory fit between the observed and predicted values; (b) the P-P curve of residuals compares the empirical cumulative distribution of residuals with the theoretical cumulative distribution of a normal distribution, further affirming the adherence of residuals to a normal distribution pattern. Second, considering that the data utilised in the study were derived from multiple individuals and arranged chronologically, two alternative statistical techniques were applied to analyse the relationships mentioned above: the random effects model and the fixed effects model (Das et al., 2017; Ren & Nickerson, 2019). The results, as shown in Table 4.8, revealed consistent findings with the previous analysis, bolstering the validity and resilience of the models used in the study.

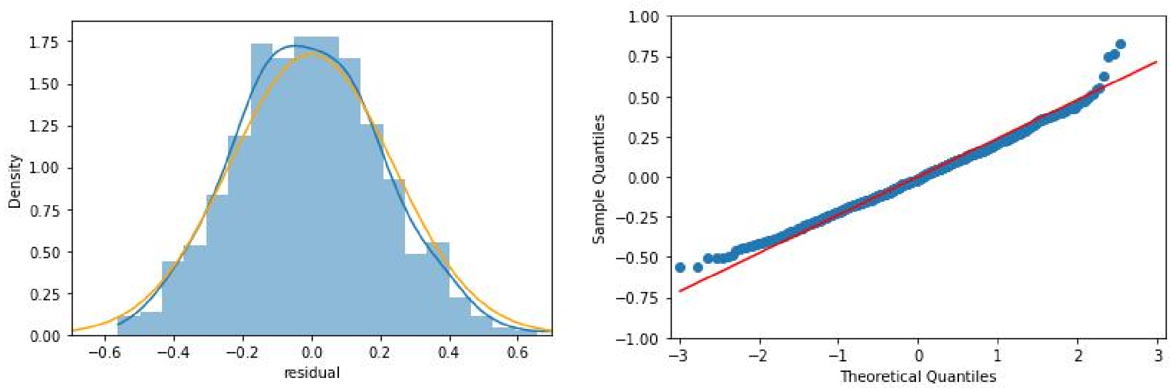


Figure 5.2 Robustness Check

Table 5.8 Robustness Check

Variables	Random effect model	Fixed effect model
Control variables		
Reply count	0.0001	-0.0001**
	(0.0000)	(0.0000)
Share count	0.0000	0.0000
	(0.0000)	(0.0000)
Like count	0.0000	0.0000
	(0.0000)	(0.0000)
Government response index	0.0001	-0.0108***
	(0.0008)	(0.0011)
Independent variables		
MISINFO	0.1081***	0.0403*
	(0.0398)	(0.0360)
ME_RP	2.2152***	1.2405***+
	(0.2378)	(0.2248)
MI_RP	0.0042***	0.0013
	(0.0008)	(0.0008)
MA_RP_E	0.0004***	0.0006***
	(0.0001)	(0.0001)
MA_RP_C	0.0170**	0.0332***
	(0.0084)	(0.0076)
MA_RP_G	0.0011**	0.0017***
	(0.0005)	(0.0005)
MA_RP_O	1.3752***	0.7453***
	(0.0617)	(0.0767)
MISINFO*ME_RP	-0.0137***	-0.0088***
	(0.0017)	(0.0016)
MISINFO*MI_RP	0.0001***	0.0001*
	(0.0000)	(0.0000)
MISINFO*MA_RP_E	-0.0000**	-0.0000***
	(0.0000)	(0.0000)
MISINFO*MA_RP_C	-0.0004***	-0.0002***
	(0.0001)	(0.0001)
MISINFO*MA_RP_G	-0.0000**	-0.0000**
	(0.0000)	(0.0000)
MISINFO*MA_RP_O	-0.0065***	-0.0041***
	(0.0006)	(0.0006)
R^2	0.54	0.56
F	67.67***	53.40***

Note: MISINFO: the diffusion of misinformation, MA_RP_E: macro-level risk perception (economy), MA_RP_C: macro-level risk perception (climate), MA_RP_G: macro-level risk perception (geopolitics), MA_RP_O: macro-level risk perception (overall global stability), ME_RP: meso-level risk perception, MI_RP: micro-level risk perception. Standard errors are reported in parentheses.

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

5.6 Discussion and Conclusion

5.6.1 Mian Findings

The study aims to address the impact of misinformation diffusion on individuals' motivations to safeguard themselves during crisis situations with varying levels of risk perceptions, as well as the consequential influence on the effectiveness of government policies. It responds to the need for considering risk perceptions within the domain of misinformation and incorporating them in a more granular dimension into the investigation of crisis management (Naeem & Ozuem, 2022; Qiao et al., 2023; Tang et al., 2021). Key findings are summarised as follows.

First, the diffusion of misinformation engenders an adverse influence on the efficacy of government policies. This observation aligns with previous research findings that have indicated a substantial escalation in the probability of the general public being influenced by distortions of government policies and partaking in mislead behaviours, thereby impeding the overall performance of policies (Islam et al., 2023; Karanasios, 2022; Lewandowsky et al., 2012).

Second, the moderating role of risk perceptions in shaping the performance of government policies is investigated at a more nuanced level in the context of the prevalence of misinformation circulated during times of crisis. In particular, both macro-level and meso-level risk perception amplify the strength of the negative association between misinformation diffusion and government policy performance. However, with increasing meso-level risk perception, the detrimental impact on government policy performance is mitigated. These distinct influences of risk perception have manifested in diverse decision-making processes associated with risk and assessment of the ability to execute recommended courses of action, consequently resulting in varying impacts on the implementation efficiency of the communicator's recommendations (Boss et al., 2015; Herath & Rao, 2009; Yoo et al., 2021).

5.6.2 Theoretical Implications

This study offers implications for future research into misinformation diffusion and risk management during times of global disruption and crisis.

First, by integrating PMT into the framework of misinformation diffusion and government policy during crises, the study enabling us to gain deeper insights into the intricate risk processing that underlie individuals' responses to government policies for crisis management. Therefore, the research underscores the strategic value of PMT in navigating the complex interplay between misinformation and policy implementation, so that yielding novel contributions to the existing body of knowledge in risk communication. As highlighted in pertinent literature (Kellens et al., 2013; Vieira et al., 2022), the absence of a universally applicable measure of risk perception for different hazards and disciplines implies that further research is required to identify and delineate the specific dimensions of risk perception within distinct domains. In this regard, the innovative application of PMT through multifaced risk perception construct can aid researchers in gaining insights into how individuals perceive and assess risks in a more granular manner. This approach holds substantial potential for informing the design of preventive actions and the development of two-way communication strategies in public health messaging, greatly benefiting efforts in risk management (Qiao et al., 2023). It is noteworthy that the challenge of risk communication often arises from the misalignment between expert opinions and public perceptions, leading to suboptimal performance in conveying recommendations by communicators (Posey et al., 2014). Successful risk communication efforts, with the objective of conveying health precautions to the public and ultimately improving pandemic-handling practices in pandemic crisis management, heavily hinge on adopting an interactive, two-way exchange dialogue between communicators, including the information sender (the government) and the information receivers (citizens) (Posey et al., 2014; Renn et al., 2011). Notably, each side should respect the insights and intelligence of the other. In the study, this study centres the attention on analysing misinformation originating from social media discussions, specifically through the perspective of ordinary citizens processing information about surrounding risks and subsequently responding to government policies. Through this research, this study can provide valuable insights that can be channelled back to the government, fostering a mutually beneficial two-way interaction. Consequently, the exchange of information would guide the refinement and enhancement of risk communication strategies, thereby bolstering the efficacy of pandemic management efforts and countering misinformation dissemination. Overall, the study leads to theoretical progression by offering a more comprehensive understanding of people's pandemic-risk perceptions and their adaptive behaviours.

Second, the study makes a valuable contribution to an unexplored research area by delving into the distinct moderation effects of various risk perceptions on a granular level, by distinguishing between different risks under threat appraisal and coping appraisal situations. Given that risk perceptions are inherently subjective (Posey et al., 2014), the findings offer insights into the potential reasons why individuals might be susceptible to misinformation under certain risky circumstances, while demonstrating resilience against its influence in other instances. This comprehension of subjectively transferring risks into the final decision-making process differs significantly among macro-, meso-, and micro-level risk perceptions. When confronted with risks at the macro- and meso-levels, individuals are more likely to prioritise the evaluation of the risk itself by assessing the perceived severity of a threatening event and the perceived probability of its occurrence, as indicated by the threat appraisal in PMT (Bubeck et al., 2018). In such circumstances, with an increased macro- and meso-level perceived risks, people are likely to engage in risk-avoiding behaviours by adhering to government policy guidelines to protect themselves and are less inclined to participate in potential misinformation discussions. Such behaviour effectively hinders the dissemination of misinformed messages through social networks, thus mitigating the adverse impact of misinformation diffusion on government policy performance. This explanation aligns with the principles of the widely accepted prospect theory, which emphasises decision-making based on perceived risks (Kahneman & Tversky, 2013). Moreover, it has been observed that individuals evaluate risk assessment simultaneously with their proposed responses to risk (Tang et al., 2021), suggesting that they may exhibit diverse reactions to risk perceptions. the research has substantiated this by finding that micro-level risk perception can significantly exacerbate the detrimental effects of misinformation propagation on the performance of government policies. This phenomenon can be explained by the coping appraisal in PMT, which centres around the evaluation of one's own capabilities and the available resources to deal with risks (Bubeck et al., 2018). When individuals hold the belief that risks are manageable given their perceived abilities, even in the presence of heightened risks, they may be less inclined to comply with rules and instead engage in more risk-seeking behaviours (Ewart, 1991; Hirschi, 2015; Inouye, 2014). Consequently, these behaviours, including promoting misinformed behaviours from unverified sources, are highly likely to contradict government policy guidelines, thereby exacerbating the adverse impact of misinformation diffusion on government policy performance. Taken together, when considering risk perception, macro-level risks extend beyond an individual's immediate influence and meso-level risk perception involves navigating complex interpersonal dynamics, both of which elude easy management through individual capabilities alone. So, individuals may opt to centre their attention on the risks themselves. In contrast, micro-level risks are more readily manageable as they primarily emanate from personal perceptions and do not depend on the involvement of others, thereby potentially leading individuals to perceive their abilities to mitigate risks as sufficient. Recognising this, the research has extended the prior literature (Kahneman & Tversky, 2013) by showing that it is not merely a matter of increased risk triggering risk-avoiding behaviours and decreased risk prompting risk-seeking behaviours, but rather, the key aspect lies in how individuals react to risks when confronted with varying levels of risk, which is in line with the previous finding proposed by Wachinger et al. (2013)'s risk paradox. This nuanced comprehension of risk perceptions would serve as a guiding principle for devising precise crisis management interventions to mitigate pandemic impacts and also inspire future research to explore coping strategies, aiming to improve risk communication by adopting appropriate coping mechanisms during crisis events.

Third, the study contributes to risk governance model by providing more nuanced evidence-based insights into the risk evaluation process, addressing the call for understanding risks by considering both risk perceptions from individuals, groups, or society and the broader social implications of consequences (Klinke & Renn, 2021). The International Risk Governance Council has proposed a risk governance model with additional adaptive and integrative capacity that embodies risk analysis and governance, structured across four phases: pre-assessment, interdisciplinary risk estimation, risk evaluation, and risk management (Renn, 2009; Renn et al., 2011). the study has notably advanced to the step of risk evaluation. More explicitly, this study embarks on an exploration of highly contextualised practices aimed at evaluating with risks within the realm of government crisis management, with a particular focus on pandemics, to propel the development of more robust and flexible risk governance strategies. This context-sensitive perspective is endorsed by the risk governance model, aiming to enhance its adaptability and veering away from the confines of a rigid and universally applicable framework (Renn et al., 2011). Besides, the risk measurement is established upon people's daily risk perceptions that are typically shaped by the integration of cultural values and worldviews. These beliefs play a crucial role in risk evaluation by effectively complementing and rectifying biases inherent in scientific evidence, particularly regarding pure cause-effect relationships in hazard potential, highlighting that risks can never be evaluated through evidence alone (Goldstein & Keohane, 1993). By understanding the diverse human judgements about risks, the study serves to enhance risk evaluation by facilitating more reasonable intervention decisions for dealing with risks in the public interest (Goldstein & Keohane, 1993; Renn et al., 2011). Furthermore, the research has advanced the assessment of multidimensional risk perceptions derived from the effective utilisation of diverse resources. This achievement facilitates the formulation of tailored risk mitigation strategies to enhance the flexibility of risk governance institutions in addressing misinformation, consequently lending support to the cultivation of an adaptive and integrative risk governance model (Chatterjee et al., 2020; Renn et al., 2011). Taken together, such enhancements to risk governance can further translate the core principles of governance into the realm of risk-related policymaking, allowing policymakers to assess relevant risks and benefits more accurately and, subsequently, engender a more dynamic and adaptive policy design (Aven & Renn, 2018).

5.6.3 Practical Implications

The study also offers practical implications for policymakers and social media operators in navigating surrounding risks to combat misinformation, thereby enhancing the efficacy of government management policies during periods of exceptional crisis.

First, the research highlights the crucial role of countering misinformation in optimizing the efficacy of government policies (Islam et al., 2023). Considering this, the immediate implication involves systematically compiling, summarizing, or archiving misinformation to facilitate policymakers' further analysis of misinformed topics, thereby enhancing the effectiveness of policy implementation. Furthermore, the absence of robust record-keeping and documentation methods has led to a lack of awareness regarding potential associations between misinformation and suboptimal policy implementation, thus exacerbating the ineffective implementation of policy directives (Alhawari et al., 2012; Irani et al., 2005). To address these issues, this study proposes establishing a comprehensive real-time information repository, curated to preserve and disseminate up to date misinformation about government policies. This repository could be structured to capture dynamic social media discussions, encompassing experiential insights into specific policies, the validation of expertise, and the public's perceptions and sentiments towards policy measures. This way, it offers policymakers a more flexible and evidence-rich tool to make well-informed policy decisions. In particular, this repository can be initiated through electronic focus group discussions, as a useful means for establishing the current state of misinformation management, particularly when first detecting misinformed opinions concerning government policies (Nielsen & Graves, 2017). This approach can lead to a comprehensive research report that identifies the misinformed topic, its source, and potential impacts on the administration process, thereby assisting policymakers in avoiding potential duplicates and exploring examples of best practises to effectively address misinformation. Further, the repository can be interconnected with pertinent public management departments, such as the public health department, particularly during pandemic crises. This linkage facilitates the presentation of accurate information and scientific knowledge on a particular misinformed topic. By maintaining an updated list of frequently occurring misinformed topics, this collaboration can swiftly adapt the misinformation mitigation process, ensuring the provision of up-to-date true information to counter the rapidly evolving nature of misinformation. Collated knowledge from expertise is then stored in the repository, streamlining future projects and enhancing overall efficiency by leveraging past successes to minimise response time and reduce rework (Alhawari et al., 2012). In addition, a real-time update is suggested, as it can ensure the accuracy and relevance of misinformed topics concerning government policies. Policymakers could largely benefit from such a structure to increase the effectiveness of their operations and launch tailored deployments of relief aid based on the interests expressed by those affected by the policies (Gour et al., 2022). Consequently, the implementation of such repository has the potential of iteratively mitigating the probability of misinformation, consequently raising the probability of successfully executing government policies.

Second, the findings substantiate the moderation role of risk perceptions in shaping policy implementation, highlighting its varying impacts. This nuanced understanding has emphasised the importance of comprehending the heterogeneous nature of risk perception for crafting effective risk communication strategies, as individuals tend to subjectively perceive and respond to risks (Kellens et al., 2013). Accordingly, this study has proposed several suggestions for policymakers and public health authorities to design clearer and more targeted risk communication approaches, ultimately reducing ambiguity and enhancing policy implementation. Given the widespread acknowledgment that risk communication can strengthen people's risk perception and motivate them to take preventive actions for emergency cases, it is necessary to address macro- and meso-level risk perception through a well-crafted risk communication campaign supported by appropriate resource allocation and cross-sector collaboration (Susha et al., 2023). Through optimizing resource allocation, policymakers can effectively communicate to the public the importance of addressing risks with objectivity. This fosters a concentrated adherence to government policies, ensuring continuous compliance without hesitation or concern. Consequently, this facilitates effective policy implementation, mitigating potential complications arising from misinformation. Concurrently, cross-sector collaboration aimed at deciphering macro- and meso-level risks perception would promote the adoption of similar adaptive strategies among individuals, thereby instilling a rational and compliant attitude towards government policies for addressing the pandemic crisis (Florin & Bürkler, 2017; Renn et al., 2011). On the other hand, it is imperative to not overlook the effective management of risks perceived at the micro-level, as prioritizing individual preparedness is paramount in risk communication (Kellens et al., 2013; Kreibich et al., 2009). Based on the findings, risks perceived in micro-level should be mitigated. Policymakers are advised to emphasise accurate information provision to counteract micro-level risk perceptions embedded within various aspects of general living and working conditions (Göran & Whitehead, 1991). This way, policymakers can systematically collect similar concerns, which can then be addressed by providing accurate explanations through the government's official website. This matching mechanism can reduce the likelihood of erroneous searches, thereby enhancing the efficiency of risk mitigation efforts and improving the performance of policy implementation. Taken together, these risk communication strategies would proficiently respond to risks at various levels.

Third, the study effectively harnesses various online media platforms, yielding insights into government policy performance for enhanced crisis management. Therefore, it is crucial to recognize that the development and widespread adoption of diverse online media tools can precipitate transformative changes in the domain of information communication practices within crisis management (Elbanna et al., 2019). This significance embodies a social resilience mindset, particularly in contexts pertaining to political efficacy, as a means to bolster the efficacy of crisis management endeavours (Heeks & Ospina, 2019; Sakurai & Chughtai, 2020). To achieve this goal, this study advocates for the integration of official information dissemination into individuals' daily leisure activities through podcast platforms (like Apple Podcasts or Google Podcasts) and discussion forms (like Reddit or Quora). By strategically promoting reliable information on these platforms, individuals are likely to be more persuaded and can access accurate information more readily and directly, thereby mitigating the risks associated with encountering misinformation. This suggestion also has the potential to increase citizens' confidence in trusting authorities and expertise can reduce susceptibility to risks at the micro-level, thus mitigating the negative impact of misinformation during crises (Bélanger & Carter, 2008; Kim et al., 2008). Besides, this study recommends that government official social media accounts incorporate a dashboard of valuable posts accompanied by a list of top information providers, which will assist with crisis recovery instructions, charity donations, and other crisis management operations (Guo et al., 2021). Then policymakers can invite information providers to volunteer in promoting accurate messages to the public through suitable channels. This approach aligns with the principle of adaptation to disruptions and is geared towards adapting to evolving situations (Boh et al., 2023; Janssen & Van der Voort, 2020). With government recognition, this adaptive collaboration can ensure stability and accountability between government and non-government actors (Elbanna et al., 2019; Janssen & Van Der Voort, 2016, 2020). Therefore, the study contributes to the emerging research on the influence of public perceptions on risk in political endeavours, serving as an inspiring foundation for future research seeking to explore additional approaches to bolster resilience in crisis management.

5.7 Limitations and Future Direction

This study has acknowledged a few limitations in the work that can help guide future research in this important domain. First, the current results are limited to the availability and quality of social media data. Given the new concerns around privacy, social media platforms are developing new controls and barriers, consequently impeding the ease of accessing free data and narrowing the scope of available information through application programming interfaces (APIs) (Suarez-Lledo & Alvarez-Galvez, 2021). Future studies may thus necessitate the exploration of alternative sources and methodologies, such as incorporating data from online forums, blogs, news articles, and even publicly available government datasets, or developing innovative scraping techniques to extract relevant data from various online platforms. Throughout the entire process, ethical considerations should guide data collection and analysis, ensuring privacy concerns are respected. Second, due to the continuous evolution of the internet, the nature of misinformation diffusion during crises may exhibit distinct attributes. This study is a snapshot of local government practises at a specific moment in time. Future studies can build on this research by exploring different types of crisis events, increasing the sample size of the study population, and enlarging the range of the study period. Such investigations would contribute to a more granular understanding of the dynamics of misinformation propagation and foster the development of effective strategies and countermeasures to mitigate the adverse impacts of misinformation during crises. Third, from a methodological perspective, the findings primarily stem from a text analysis with the aim of classifying and analysing misinformation on social media. Consequently, this study has overlooked behavioural expressions among individuals in decision-making. Thus, future studies could conduct behavioural experimental studies to understand how misinformation affects people's behaviour and, consequently, their decision-making during crises.

Chapter 6. Conclusions and Future Research

This chapter section will primarily encompass three components. Firstly, the key findings of the thesis (Section 6.1) will be elucidated by revisiting the research questions and objectives, accompanied by a comprehensive summary of the conclusions. Secondly, an overarching discussion will be presented, integrating all aspects of the paper to elaborate on the theoretical contributions (Section 6.2.1) and practical implications (Section 6.2.2). Lastly, limitations will be addressed to enhance the rigor of the thesis and contribute to potential future research avenues, as outlined in Section 6.3.

6.1 Key Findings

In general, the thesis explored the dynamics influencing the implementation of government policies in the context of the COVID-19 crisis in the UK, promoting a deeper comprehension of influential factors, including public emotions, misinformation diffusion, and public risk perceptions.To echo the overall objective of the thesis, which is to investigate the factors that influence the performance of government policies, this thesis has identified several key areas from the perspective of public attributes that were previously overlooked. Specifically, it has uncovered the mediating mechanisms of public emotions, contributors to misinformation, and the varying effects of different types of risk perceptions among the general public. Together, these components form a comprehensive narrative that demonstrates how policies have been affected in ways that were previously unrecognized when investigating the influencing factors of policy performance. This thesis contributes significantly to the fields of public management and information systems by providing new insights into the complex dynamics that shape policy implementation during crises.

In more detail, Chapter 3 of the thesis delves into the specific areas identified in the overall objective. It has identified a plausible role of emotions, particularly *fear* and *surprise*, serving as mediators in the context of government policies and their subsequent outcomes in pandemic management. This finding pertains to the first research question, which examines how the stringency of policies influences public emotions, ultimately impacting the effectiveness of policy implementation. Furthermore, Chapter 4 aims to exam the various sources and channels through which misleading information can spread, and it has revealed a negative correlation between user engagement, the frequency of specific content topics (such as face protection, international economic support, and screening methods), and the dissemination of misinformation. This finding aids in understanding the factors influencing the spread of misinformation. Besides, government management policies exhibited varying moderating effects on misinformation diffusion, depending on their characteristics. These findings correspond to the second research question, which focuses on identifying the significant factors that influence the dissemination of misinformation regarding government policies. In addition, Chapter 5 found a detrimental impact of misinformation diffusion on the effectiveness of government policies during crises and this deleterious impact could be alleviated through heightened macro- and meso-level risk perceptions but exacerbated by an escalation in micro-level risk perception. This intriguing discovery aligns with the final research question, which explores how risk perceptions can shape individuals' responses to policies and their overall willingness to comply with them, aiming to identify potential solutions for policymakers to shape public opinions by managing these perceptions during a crisis.

6.2 Discussions

This subsection will provide the theoretical contributions and practical applications based on the findings mentioned above. It will highlight the interplay between these two dimensions and demonstrate their mutual importance for a comprehensive understanding of the factors that contribute to government policies' performance from the perspective of the general public.

In general, all of the paper chapters in this thesis have made significant contributions to the literature in the fields of AIT, ELM, and PMT by uncovering previously overlooked aspects of these frameworks. They have highlighted the managerial value of public emotions and risk perceptions embedded in social media messages, as well as the social value of misinformation that can be extracted from these messages. By converting text data into more valuable formats, these papers have significantly contributed to the understanding of how to improve government policy performance. Additionally, by leveraging social media data, readers have gained insights into how the public perceives and responds to various policies and events. This information is invaluable for policymakers, as it can help them make more informed decisions, refine strategies, and improve communication with the public.

Furthermore, the papers have presented agile managerial strategies that are both efficient and time-saving. These strategies can help policymakers deal more effectively with public events and crises by allowing them to quickly assess the situation, identify key issues, and develop appropriate responses. This agility is particularly important in today's fast-paced and interconnected world, where events can unfold rapidly and have widespread impacts. Overall, the contributions of these paper chapters are significant, not only possessing academic value but also practical value for addressing public concerns and achieving policy goals

6.2.1 Theoretical Contributions

This thesis has contributed significantly to the theoretical landscape, advancing the understanding of how public attributes contribute to effective policy implementation within the domains of Information Systems and Public Management literature. Specifically, the outcomes of Chapter 3 substantiate the pivotal role of public emotions, suggesting their potential to yield diverse impacts on the political decision-making of individuals, as highlighted by the influence they exert on the unfolding of political events (Marcus et al., 2011). This answers the call of the importance of gaining an updated understanding of emotions in the context of public health crisis (Han & Baird, 2022). Overall, it has enriched the field of public management by discerning managerial insights from emotional cues embedded in social media messages and provided invaluable perspectives on the effective containment of infectious diseases, ultimately alleviating their deleterious effects on the government policy implementation and public health infrastructure (Han & Baird, 2022; Zheng et al., 2023). Moreover, Chapter 4 captures diverse and novel patterns observed within the realm of misinformation pertaining to government policies amid crisis scenarios, thereby making a significant contribution to the emerging body of research on information system management (Feng et al., 2021). Notably, this revelation underscores the dynamics of information propagation, emphasizing the bidirectional flow of information between citizens and governing bodies, thereby enhancing the cultivation of a more interactive and reciprocal form of communication in government-citizen interactions, ultimately benefiting the implementation of government policies (Guan et al., 2021). Furthermore, Chapter 5 offers a more comprehensive interpretation of risks within crisis scenarios, bringing the analysis closer to real-world applications (Wachinger et al., 2013). These findings provide valuable insights into unravelling the paradox of risk perception within the framework of government crisis management policies, elucidating the susceptibility of individuals to misinformation under specific circumstances, while highlighting their resilience against its influence in divergent scenarios.

6.3 Practical Implications

Meanwhile, practical implications are provided by the thesis to bring benefits to policymakers and social media operators. In Chapter 3, the study primarily provides recommendations for policymakers and social media operators to collaborate in implementing a sentiment engine that links the reproduction number with real-time emotion monitoring, particularly within the framework of public health policy formulation. Functioning as an agile auxiliary to minimize time expenditure, this approach surpasses the constraints of solely tracking the reproduction number, thereby offering a more efficient mechanism for promptly alerting policymakers about critical situations (Lai, 2018). Consequently, strategic recommendations can not only foster the augmentation of the rapid response capacity of the public health system but also establish an environment conducive to successful public management through the promotion of enhanced policy compliance (Zheng et al., 2023). Moreover, the suggestions in Chapter 4 predominantly focus on strategies to mitigate the spread of misinformation, which necessitates distinct approaches compared to those employed for managing the dissemination of general information. To effectively manage the diffusion of misinformation regarding government policies during crises, this study recommends enhancing user engagement through a two-way communication channel, with a focus on providing more precise information of protective behaviours and fostering improvements in public trust (Allington et al., 2021; Guan et al., 2021; Laato et al., 2020). Besides, the identification of various moderating effects of government policies provides policymakers with tailored recommendations and guidelines intended to bolster their effectiveness in managing crises (Driss et al., 2019). Furthermore, in Chapter 5, the study mainly offers suggestions for policymakers and public health authorities to develop more nuanced and actionable risk communication strategies, taking into consideration the diverse nature of the public's risk perception (Kellens et al., 2013). Implementing these risk communication strategies would foster the development of a more comprehensive and proactive society, adept at effectively addressing risks across various levels, particularly in the face of the influence of misinformation diffusion during crises.

6.3 Limitations and Future Research

As with any research, this thesis has some limitations, which could provide fruitful avenues for future research. First, the thesis solely emphasizes emotional reactions, necessitating a more comprehensive future investigation to integrate emotional reactions and behavioural factors, alongside unforeseen situational variables within a given public event. This approach would provide more well-rounded insights and tools for policymakers to design, implement, and adapt policies, thereby enhancing the resilience of public management systems. Second, the constrained focus on the misleading information could potentially overshadow the significance of the diffusion of verifiable and accurate information in influencing the implementation of government policies. So, future research is encouraged to emphasize this specific aspect, thereby uncovering additional patterns within the realm of information systems. Third, the risks elucidated in the thesis primarily stem from data science techniques applied to text data, inadvertently overlooking other manifestations of risk perception expressed through alternative channels, such as risk perception surveys, questionnaires, and various risk assessment protocols (Allan, 2006; Kaptan, Shiloh, & Önkal, 2013). Thus, future studies could endeavour to conduct a more comprehensive examination by incorporating diverse methodologies to capture a broader spectrum of risks and their implications in public management decision-making processes. Fourth, this thesis exclusively concentrates on data derived from the UK. Collecting data from other regions and nations could serve to fortify the hypotheses and conclusions of this research, thereby enabling a more comprehensive perspective. Future studies could leverage data from various countries, including the United States and China, where a substantial body of research on the effects of emotions exists. Finally, the thesis is constrained by the access to social media data. With the growing emphasis on privacy, social media platforms are implementing new safeguards and limitations, thereby hindering the unrestricted acquisition of data and limiting the range of accessible information through application programming interfaces (APIs) (Suarez-Lledo & Alvarez-Galvez, 2021). Future endeavours may require the exploration of alternative sources and methodologies, such as incorporating data from online forums, blogs, news articles, and even publicly available government datasets. Innovative scraping techniques could also be developed to extract pertinent data from a diverse array of online platforms.

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Appendixes

Appendix 1. Explanation of Key Variable Measurement

We offer more details regarding the meaning of the data is essential to make the 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., 2020).

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:

0 - no measures

1 - recommend closing or all schools open with alterations resulting in significant differences compared to non-Covid-19 operations

2 - require closing (only some levels or categories, e.g., just high school, or just public schools)

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 1, 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, this study offered the github link for equation 1, as follow: https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/index_methodology.md.

Appendix 2. An example of COVID-19 Fake News Detection

ID	Tweets	Label
1	The CDC currently reports 99031 deaths. In general the discrepancies in death counts between different sources are small and explicable. The death toll stands at roughly 100000 people today.	real
2	States reported 1121 deaths a small rise from last Tuesday. Southern states reported 640 of those deaths. https://t.co/YASGRTT4ux	real
3	Politically Correct Woman (Almost) Uses Pandemic as Excuse Not to Reuse Plastic Bag https://t.co/thF8GuNFPe #coronavirus #nashville	fake
4	#IndiaFightsCorona: we have 1524 #COVID testing laboratories in India and as on 25th August 2020 36827520 tests have been done : @ProfBhargava DG @ICMRDELHI #StaySafe #IndiaWillWin https://t.co/Yh3ZxknnhZ	real

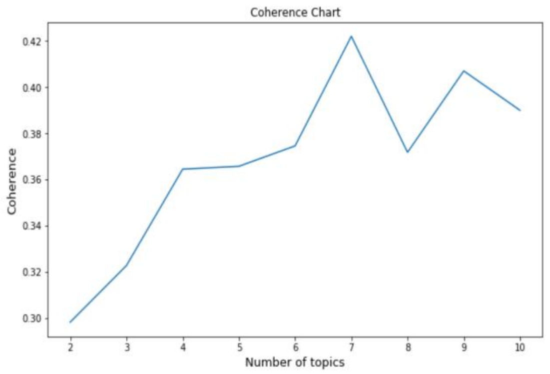
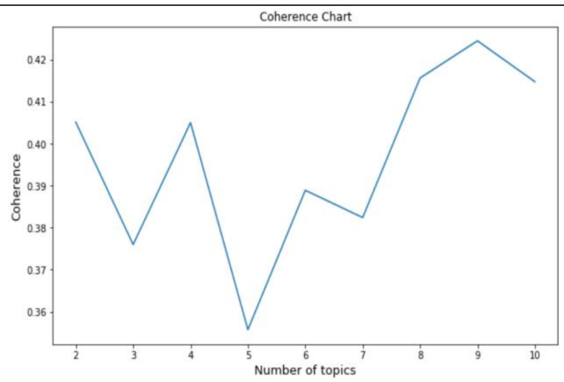
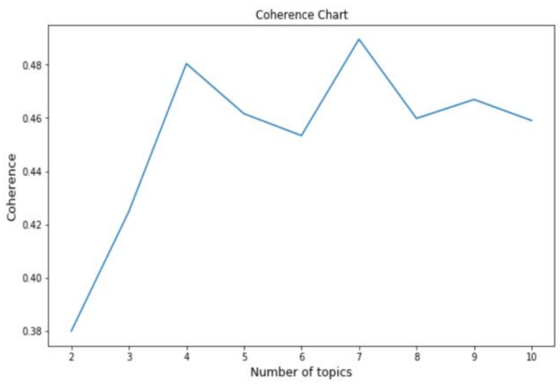
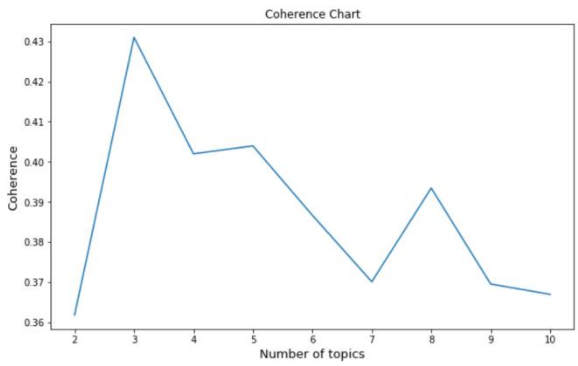
5	Populous states can generate large case counts but if you look at the new cases per million today 9 smaller states are showing more cases per million than California or Texas: AL AR ID KS KY LA MS NV and SC. https://t.co/1pYW6cWRaS	real
6	Covid Act Now found "on average each person in Illinois with COVID-19 is infecting 1.11 other people. Data shows that the infection growth rate has declined over time this factors in the stay-at-home order and other restrictions put in place." https://t.co/hhigDd24fE	real
7	If you tested positive for #COVID19 and have no symptoms stay home and away from other people. Learn more about CDC?€?s recommendations about when you can be around others after COVID-19 infection: https://t.co/z5kkXpqkYb. https://t.co/9PaMy0Rxaf	real
8	Obama Calls Trump?€?s Coronavirus Response A Chaotic Disaster https://t.co/DeDqZEhAsB	fake

Appendix 3. Model Selection Results

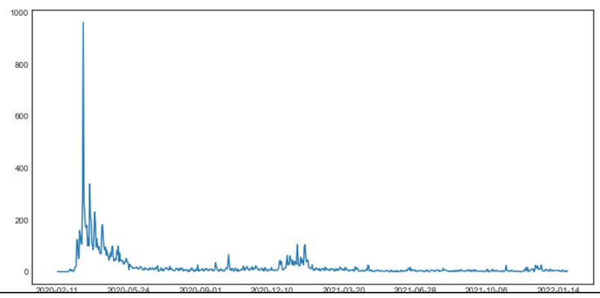
Model selection	Precision	Recall	F-1 score	accuracy	AUC (area under curve)
Logistic regression	92%	97%	94%	94%	98%
Naive Bayes	87%	97%	92%	91%	97%
Support Vector Machines	81%	87%	84%	82%	82%

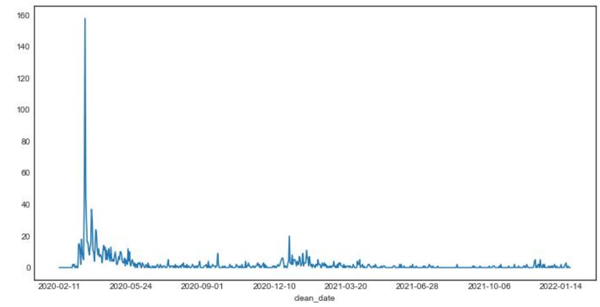
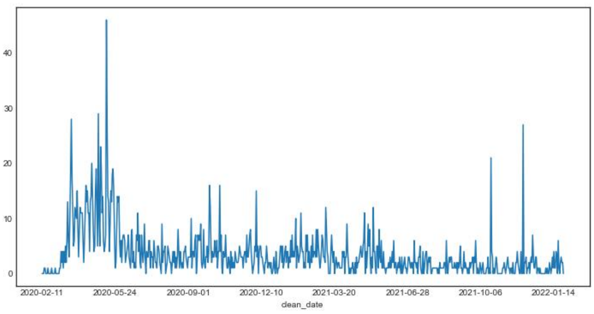
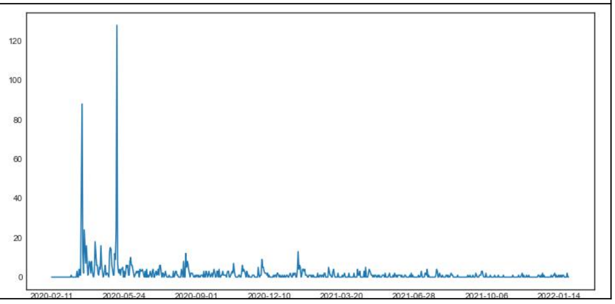
Appendix 4. Coherence Charts for Optimal Number of Topics

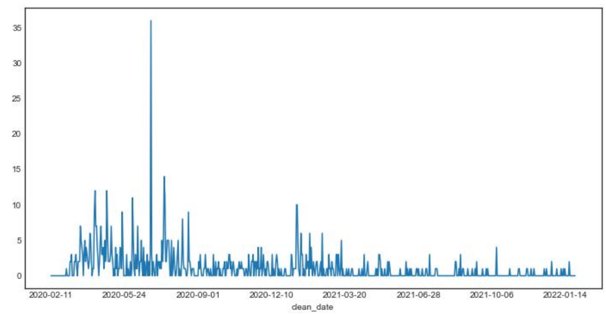
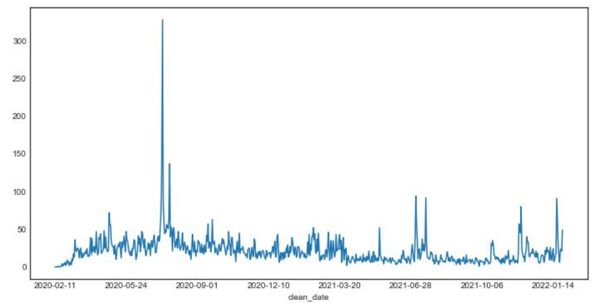
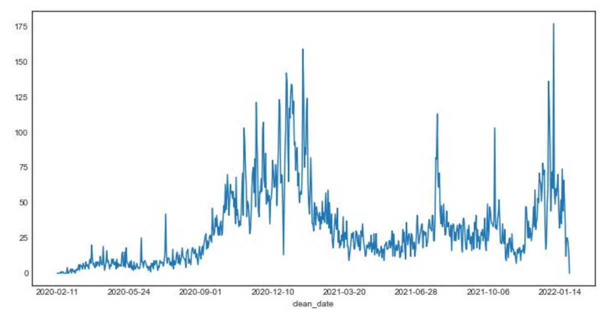
The optimal number of topics for each policy-related text is determined. Containment policy-related texts have seven optimal topics; economic policy-related texts have nine; health policy-related texts have seven; and vaccination policy-related texts have three. In total, 26 topics are discovered originally.

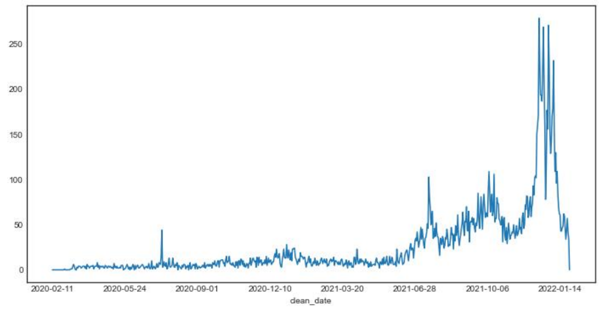
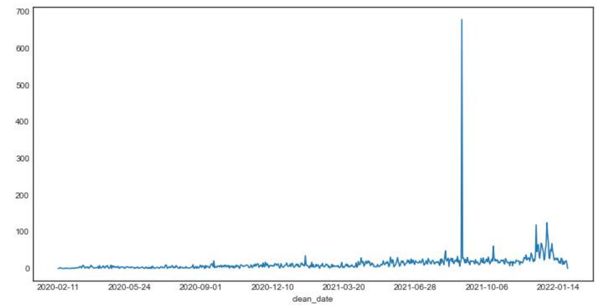
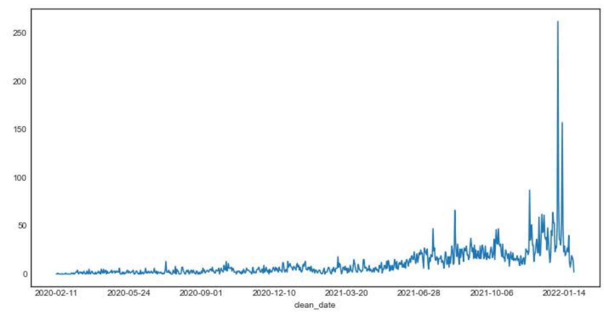
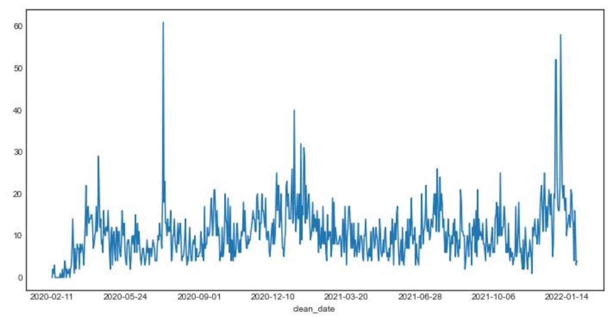
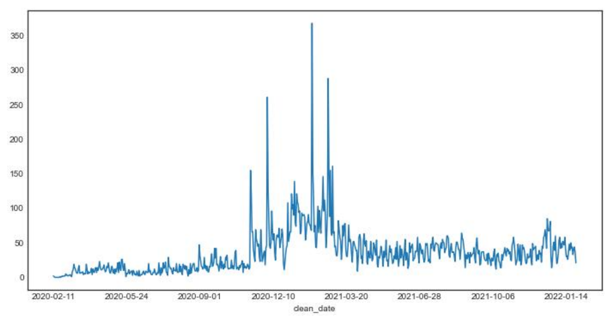
Text category	Coherence chart	Text category	Coherence chart
Containment policy	 Figure 3.1 Coherence Chart of Containment Policy-Related Texts	Economic policy	 Figure 3.2 Coherence Chart of Economic Policy-Related Texts
Health policy	 Figure 3.3 Coherence Chart of Health Policy-Related Texts	Vaccination policy	 Figure 3.4 Coherence Chart of Vaccination Policy-Related Texts

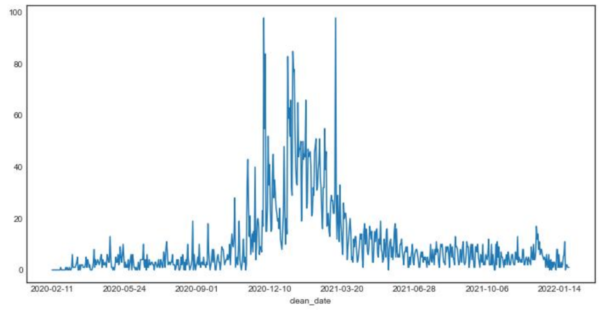
Appendix 5. Topic Modelling Results

ID	Content topics	Keywords	Topic descriptions	Topic distribution over time
1	content topic 1 daily routine changing	'event, cancel, safe, spread, decide, listen, live, world, together, hope',	cancelling events	
2		'stayathome, amp, staff, outbreak, good, show, last, learn, give, late',	stay-at-home, staffs are working from home	

3		'decision, follow, case, make, online, continue, public, death, family, student, team’	people’s decisions on their personal life, mostly about cancellations	
4		'lockdown, country, travel, light, parent, ban, measure, member, old, travelban',	human mobility restrictions	
5		'home, work, stay, workfromhome, pandemic, thank, support, business, time, share'	work from home	
6		'school, school_closure, new, free, quarantine, week, day, child, kid, notice',	school closure	
7	content topic 2 citizen–government relationships	'people, government, time, think, change, contact, plan, guidance, announce, nihilistic',	how people think of government's actions including guidance and announcement	
8	content topic 3 international economy support	support, international, help, business, amp, work, new, crisis, update, eligible',	support for business	
9		support, international, response, global, benefit, industry, fight, nurse',	support for industries and nurses (medical industry)	
10		support, international, student, face, launch, people, vital, continue, pandemic, useful',	support for international students (education)	
11	content topic 4 employment assistance plans	'income, support, scheme, selfemployment, grant, claim, include, seiss, people, hmrc',	self-employment for income support, mentioning HM Revenue and Customs (HMRC) and Self-Employment	

			Income Support Scheme grant (SEISS)	
12		selfemployed, detail, link, force, lockdown, huge, follow, tell, application, write',	self-employment	
13		crisis, employee, website, film, enthusiasm, significant, ideal, completely_change, views_though, close'	general employment	
14	content topic 5 national economy support	'government, relief, impact, debt, package, information, need, help, fund, emergency',	support such as relief, debt, fund for emergency	
15		relief, debt, individual, financial, call, part, response, open, info, economy',	support such as relief and debt	
16		economic, stimulus, receive, first, plan, hit, release, household, roll, budget',	the government supports livelihood and offers stimulus plan for households	
17	content topic 6 face covering protection	mask, face, wear, people, protect, spread, help, stop',	face covering protections	
18	content topic 7 infection and death	test, pcr, death, positive, people, infection, rate, result, patient, diagnose',	infection, death rate and diagnosis	

19	content topic 8 infection symptom	test, positive, negative, pcr, symptom, feel, cough, isolate ',	feelings and symptoms	
20	content topic 9 service quality	test, pcr, free, symptom, book, result, rapid, available, site, order',	service quality of screening method, mainly PCR test	
21	content topic 1 life routine changing	test, pcr, travel, need, negative, country, proof, pass, fly, check, quarantine, government, accept',	travelling and quarantine rules that belong to life routine changing.	Same as the figure in content topic 1 - daily routine changing
22	content topic 10 screening method and school operation	test, symptom, positive, pcr, school, result, lateral_flow, case ',	screening method and its operation in schools	
23	content topic 11 protect old people	health, protect, elderly, people, investment, public, patient, hospital, vulnerable, risk',	protect old people	
24	content topic 12 injection discussion	available, first, dose, appointment, receive, free, book, support, offer, pharmacy',	first dose injection, its availability and etc	
25		available, people, priority, nhs, group, health, staff, support, worker, many, become, vaccine,	vaccine injection (availability, locations, effectiveness) and who gets the	

		good',	priority	
26	content topic 13 vaccination development	'available, develop, world, public, treatment, effective, widely, global, invest, trail, scientist, drug, test, government',	people talked about the effectiveness of vaccines and its future research development	

Appendix 6. Pearson Correlation

	Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**
1	User engagement	1																					
2	Positive message framing	-0.22***	1																				
3	Negative message framing	-0.20***	0.93	1																			
4	Content similarity	0.17***	0.09**	-0.01	1																		
5	Content topic 1	-0.10***	0.29***	0.37***	-0.55***	1																	
6	Content topic 2	-0.03	0.20***	0.28***	-0.44***	0.80***	1																
7	Content topic 3	-0.14***	0.16***	0.18***	-0.49***	0.54***	0.45***	1															
8	Content topic 4	-0.09**	0.07*	0.10***	-0.38***	0.46***	0.37***	0.51***	1														
9	Content topic 5	-0.09**	0.08*	0.11***	-0.36***	0.43***	0.32***	0.46***	0.42***	1													
10	Content topic 6	-0.25***	0.39***	0.45***	-0.41***	0.39***	0.23***	0.38***	0.24***	0.32***	1												
11	Content topic 7	-0.11***	0.71***	0.67***	0.27***	-0.10***	-0.18***	-0.14***	-0.18***	-0.17***	0.15***	1											
12	Content topic 8	0.04	0.60***	0.57***	0.54***	-0.32***	-0.27***	-0.32***	-0.28***	-0.26***	-0.11***	0.61***	1										
13	Content topic 9	0.01	0.61***	0.54***	0.52***	-0.29***	-0.24***	-0.23***	-0.23***	-0.26***	-0.13***	0.59***	0.81***	1									
14	Content topic 10	0.04	0.50***	0.46***	0.55	-0.36***	-0.30***	-0.35***	-0.29***	-0.27***	-0.17***	0.52***	0.84***	0.79***	1								
15	Content topic 11	-0.13***	0.70***	0.71***	-0.02***	0.22***	0.11***	0.14***	0.08**	0.12***	0.39***	0.61***	0.41***	0.39***	0.33***	1							
16	Content topic 12	-0.13***	0.76***	0.66***	0.31***	-0.08**	-0.14	-0.07*	-0.18***	-0.15***	0.10***	0.77***	0.58***	0.61***	0.52***	0.53***	1						
17	Content topic 13	-0.11***	0.47***	0.37***	0.13***	0.06*	-0.04***	0.09**	-0.04	0.02	0.10***	0.56***	0.17***	0.26***	0.15***	0.36***	0.70***	1					
18	Containment policy	-0.14***	0.33***	0.40***	-0.57***	0.97***	0.76***	0.55***	0.44***	0.42***	0.46***	-0.05	-0.30***	-0.27***	-0.36***	0.26***	-0.02	0.12***	1				
19	Economic policy	-0.16***	0.18***	0.20***	-0.54***	0.58***	0.44***	0.89***	0.69***	0.62***	0.46***	-0.11***	-0.37***	-0.28***	-0.39***	0.18***	-0.07**	0.13***	0.60***	1			
20	Health policy	-0.19***	0.88***	0.87***	0.25***	-0.04	-0.11***	-0.08**	-0.12***	-0.08**	0.35***	0.81***	0.78***	0.73***	0.69***	0.70***	0.72***	0.36***	0.02	-0.07*	1		
21	Vaccination policy	-0.15***	0.77***	0.66***	0.27***	-0.04	-0.12***	-0.02	-0.14***	-0.11***	0.14***	0.77***	0.53***	0.57***	0.47***	0.54***	0.98***	0.79***	0.02	-0.02	0.71***	1	
22	Misinformation	-0.12***	-0.08**	-0.05	-0.11***	0.12***	0.10***	0.02	0.10***	0.08**	0.004	-0.08**	-0.14***	-0.15***	-0.17***	-0.04	-0.14***	-0.08**	0.10***	0.08**	-0.12***	-0.14***	1

Note: $*p < .1$, $**p < .05$, $***p < .01$.