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# Dynamic Insights: Unraveling Public Demand Evolution in Health Emergencies Through Integrated Language Models and Spatial-Temporal Analysis

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**Background and Purpose:** In public health emergencies, rapid perception and analysis of public demands are essential prerequisites for effective crisis communication. Public demands serve as the most instinctive response to the current state of a public health crisis. Therefore, the government must promptly grasp and leverage public demands information to enhance the effectiveness and efficiency of health emergency management, that is planned to better deal with the outbreak and meet the medical demands of the public.
**Methods:** This study employs dynamic topic mining and knowledge graph construction to analyze public demands, presenting a spatial-temporal evolution analysis method for emergencies based on EBU models. EBU models are three large language models, including ERNIE, BERTopic, and UIE.
**Results:** The data analysis of Shanghai's city closure and control during the COVID-19 epidemic has verified that this method can simplify the labeling and training process, and can use massive social media data to quickly, comprehensively, and accurately analyze public demands from both time and space dimensions. From the visual analysis, geographic information on public demands can be quickly obtained and areas with serious problems can be located. The classification of geographical information can help guide the formulation and implementation of government policies at different levels, and provide a basis for health emergency material dispatch.
**Conclusion:** This study extends the scope and depth of research on health emergency management, enriching subject categories and research methods in the context of public health emergencies. The use of social media data underscores its potential as a valuable tool for analyzing public demands. The method can provide rapid decision supports for decision-making for public services such as government departments, centers for disease control, medical emergency centers and transport authorities.
**Keywords:** public demands, spatial-temporal evolution, dynamic topic mining, health emergency management, public health emergencies

## Introduction

Recent decades have seen increasingly unpredictable outbreaks of zoonotic and emerging infectious diseases (such as SARS, Zika, Ebola, Covid), changing climate, widespread economic crises and regular outbreaks of violent conflict. The uncertainty of these crises makes it difficult to plan and meet the health needs of the populations facing them.[1] Rapid perception and analysis of public demands are essential prerequisites for effective public health crisis communication and play a pivotal role in social governance and public health emergency management. Under the "China Experience" strategy, the application of digital technologies in different stages of emergency management can effectively address the risks of public health emergencies.[2] The primary objective of public health emergency management is to reinstate normalcy in affected areas, and given the inherent complexity of public health crises, government departments must possess a comprehensive understanding of the crisis while formulating policies and programs.[3] Public demands serve as the most instinctive response to the current state of a crisis. Therefore, the government must promptly grasp and leverage public demands information to enhance the effectiveness and efficiency of public health emergency management, that is planned to better deal with the outbreak and meet the medical demands of the public.[4]



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Accurately and dynamically perceiving public demands, and responding to them accurately and timely, has emerged as a significant challenge in the field of public health emergency management. The relevant government departments or enterprises urgently need a well-structured, and intelligent emergency intelligence system supported by advanced technologies such as data analysis, artificial intelligence, and machine learning.[5] This system will assist relevant departments in acquiring timely information on public demands, accurately identifying topics from public demands data, and understanding the evolutionary path of hot topics.[6]

To combat the COVID-19 pandemic, Shanghai enforced "Territorial Static Management" starting March 31, 2022, placing the city under closed management. Throughout the period of "total static management", residents of Shanghai faced shortages and challenges in accessing medical care, daily supplies, etc., resulting in some disarray that garnered public attention. The limitations on seeking assistance through traditional feedback channels prompted intense discussions on social media, with microblogging platforms emerging as hubs for public demands. The intertwined dynamics of "epidemic, social situation, and public opinion" on these online platforms made the government to take note of online public demands. However, the vastness of the internet and the dispersed nature of demands-related content posed challenges for the government in responding and offering assistance. The absence of a timely and aligned government response risked diminishing trust in the government. The strategic integration of digital transformation into public health risk response can significantly improve crisis communication, management, and ultimately, the protection of public wellbeing during emergencies.[7]

Therefore, this study utilizes a large language pre-training model, coupled with dynamic topic mining and knowledge graph construction, to investigate the temporal and spatial evolution of online public demands. Decision-making dilemma in public management, especially the decision-making dilemma in emergency services, has presented significant challenges for relevant personnel who need to make decisions in time. This requires decision makers to have a rapid and comprehensive grasp of public information in specific environments.[4] The goal is to enhance the precision and efficiency of government responses in public health emergencies, bolster the resilience of government emergency management, address the public's needs promptly, and improve the stability of the social system during public health emergencies.

While numerous studies examine the utility of social media in emergencies, the majority focus on its role as a medium for effectively disseminating information.[8] There is a notable gap in research regarding how governments can harness social media and big data to collect and analyze public demands. Post-emergency situations often witness a rapid surge in calls for help within a short timeframe, overwhelming official emergency agencies and hindering swift responses.[9] In contrast, social media offers a novel avenue for the public to share real-time information about their needs openly. Individuals affected and requiring assistance utilize social media platforms to articulate needs such as food, shelter, and medical aid. This information becomes accessible to first responders, policymakers, and the general public, facilitating an up-to-date understanding of crisis developments.[10] A study of the 2010 Yushu earthquake demonstrated that individuals turned to Sina Weibo to seek information about emergencies or inquire about the well-being of friends and family.[11] During the 2017 Kitakyushu rainstorm disaster in Japan, the government recommended using Twitter to request help if unable to make emergency calls.[12] Consequently, many people posted tweets with the hashtag #Rescue to solicit assistance. The real-time categorization of public demands on social media has been proposed as a valuable tool for governments and rescue organizations in disaster response and recovery.[13] Sakaki et al[14] conducted disaster drills, illustrating that Twitter and other social media types significantly enhance the efficiency of search and rescue efforts by medical personnel. Abd-Alrazaq et al,[15] in a study mining Twitter platforms for the COVID-19 Outbreak-related tweets, analyzed them to unveil the top concerns of Twitter users during the outbreak. Social media information also plays a crucial role in aiding policymakers in allocating appropriate services to the public, contributing to the management and mitigation of various disaster-related information such as location, size, target, and the number of people at risk.[16]

Topic mining aims to uncover the latent semantic structure in textual data, facilitating scholars' rapid comprehension of topic distributions and their relevance within a dataset. The most commonly employed approaches include the Latent Dirichlet Allocation (LDA) model and methods that integrate other technologies based on the LDA model. LDA is a probabilistic model for uncovering hidden thematic structures within a collection of documents. It assumes that each document is a mixture of various topics, and each topic is characterized by a distribution of words.[17] Zhang et al employed the LDA model for mining topics related to online rumors during emergencies.[18] Wahid et al introduced the Topic2labels (T2L) framework in their study on Disaster Management Decision Making, proposing an automated method for labeling data through the LDA model. The framework utilizes BERT (Bidirectional Encoder Representations from Transformers) embedding to construct feature vectors for data classification based on context.[19] Wenjun et al innovatively integrated the LDA model into Density-Based Spatial Clustering with Noise Applications (DBSCAN) to explore spatial subclasses of topics. Using the 2016 hefei rainstorms and floods as an example, they combined the LDA model with Markov transfer probability matrices to quantitatively analyze the temporal evolution characteristics of fine-grained topics related to natural disasters.[20] Jing et al applied LDA topic mining to rank public topics in a study focused on large group emergency decision-making.[21] However, LDA is prone to noise and errors when analyzing social media data, and the number of topics must be specified manually. To address these limitations and capture changing features, scholars have proposed a topic model based on a pre-trained BERT model (BERTopic).[22] This model considers contextual relationships between words, enabling a better understanding of semantic information. Simultaneously, the depth language modeling algorithm in this dynamic topic modeling model enables the extraction of topic evolution trends.

Currently, BERTopic-based topic mining is predominantly employed to comprehend discussions in specific scenarios. da Rosa et al utilized BERTopic to investigate allegations of election fraud.[23] Mazzei and Ramjattan conducted a systematic literature review on machine learning in Industry 4.0 using BERTopic.[24] Bu et al introduced a customized BERTopic model to cluster the software description text of application software. By leveraging the clusters obtained from topic clustering and the extracted topic words, they achieved automatic annotation and updating of application software labels, enabling accurate software recommendations for users.[25] Yusung An et al employed BERTopic for topic modeling to categorize review data on the Korean e-commerce platform "Naver Shopping" into corresponding topics. They extracted product advantages and disadvantages from each topic.[26]

In summary, most of the existing articles are static mining from the text, while ignoring the dynamic evolution in the object text. Although the immediacy of information on online platforms is high, the content of public demands may be redundant and dispersed in emergency scenarios, and how the government can respond correctly in a timely and effective manner becomes a key issue. Therefore, this study is dedicated to a public health emergency scenario, and explores the spatial and temporal evolution of public demands by constructing an analytical model of public demands, breaking down the information barriers between the government and the public, and providing important references for government managers on how to respond to public demands and meet the actual needs of the public in a timely, accurate, and efficient manner.

## Material and Methods

In the realm of social media, public demands primarily manifest as diverse text messages posted by individuals. These messages exhibit characteristics such as varied content, irregular language usage, high timeliness, and explicit geographic information. When employing traditional machine learning methods for the analysis of the evolution of public demands, the complexity of annotation and training is elevated, requiring a substantial amount of time. Large language models, exemplified by GPT, have demonstrated the capability to streamline intricate text processing tasks into more manageable fine-tuning problems.[27] Consequently, we incorporate three prominent large language models: ERNIE 3.0, BERTopic, and UIE, as the technical foundation for the evolutionary analysis of public demands.

In this section, we elaborate on our material and methods through four stages. Firstly, we provide an overarching depiction of spatial-temporal evolution analysis method of public demand, grounded on three large language models (ERNIE, BERTopic, and UIE). Subsequently, in the second, third, and fourth stages, we delve into the specifics of our methodology by sequentially detailing Data Collection and Construction of Public demands Dataset, Topic Mining for Public demands Based on BERTopic Model, and Construction of geographic knowledge graph of public demands based on the UIE model.

### Stage 1: EBU-Based Approach to the Spatial-Temporal Evolution of Public Demands

In this study, we propose a spatial-temporal evolution analysis method for public demands in health emergencies based on three language models and encompassing both temporal and spatial dimensions, as illustrated in Figure 1. This method mainly includes three steps. The first step is to collect social media data on public demand, classify it based on ERNIE model, and annotate it based on geographic information to construct a classified public demand dataset with geotagging attributes. In this part, the core content is to use the ERNIE model to classify the dataset. Therefore, in stage 2, we have provided a detailed introduction to the specific method and detailed explanations of the model parameter settings for easy experimental

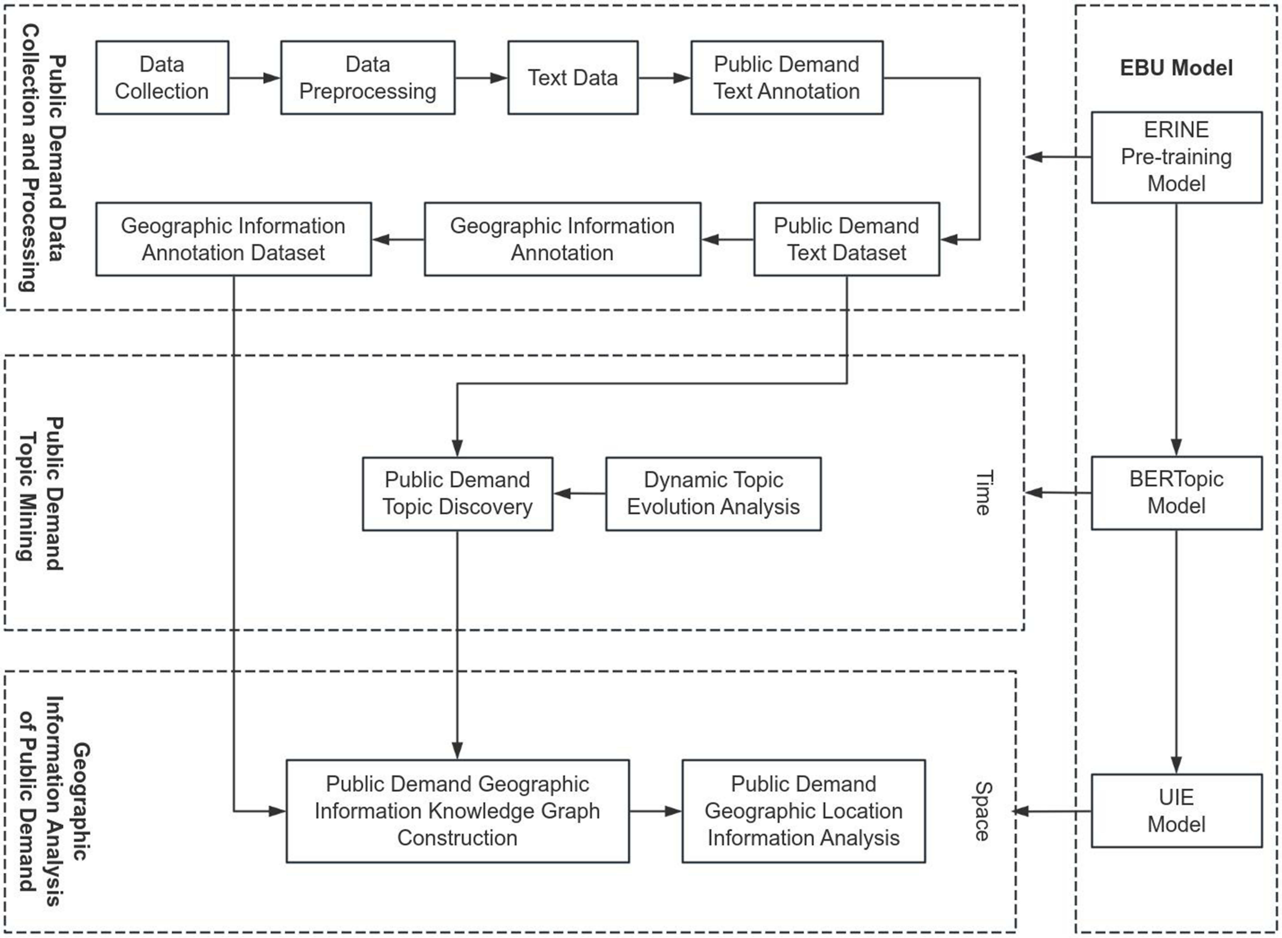


**Figure 1** EBU-based spatial-temporal evolution analysis method of public demands.

replication. The second step is to analyze public demands topics based on BERTopic model and to analyze the dynamic evolution of topics with a time series. We provide a detailed introduction in stage 3. The third step is to construct a geographic knowledge graph of public demands using the UIE model and analyze the geographic information within the public demands dataset with spatial coordinates. We provide a detailed introduction in stage 4.

## Stage 2: Data Collection and Construction of Public Demands Dataset Based on ERNIE Model

### Data Collection

This study selects the 2022 Shanghai public health outbreak as a case study. Throughout the epidemic in Shanghai, there was a surge in public demands, overwhelming traditional feedback channels that had limited capacity to respond promptly and effectively to citizens' needs. Recognizing this, Sina Weibo established the Shanghai Protest Help Superchat, providing a platform for the public to articulate their demands online. Consequently, by choosing the Shanghai epidemic as a case study, data acquisition becomes both convenient and comprehensive.

According to the white paper titled "China's Actions to Combat the COVID-19 Epidemic",[28] the Shanghai epidemic was classified into five stages, as depicted in Figure 2.

The most critical phase of the epidemic was the outbreak period, marked by a significant surge in public demands. Weibo initiated an anti-epidemic help hashtag on the evening of March 29, 2022, leading to a substantial number of public requests posted under the topic "#Shanghai anti-epidemic help#". Consequently, the original microblog data published from March 30 to April 26, 2022, containing the keyword "Shanghai anti-epidemic help", were systematically

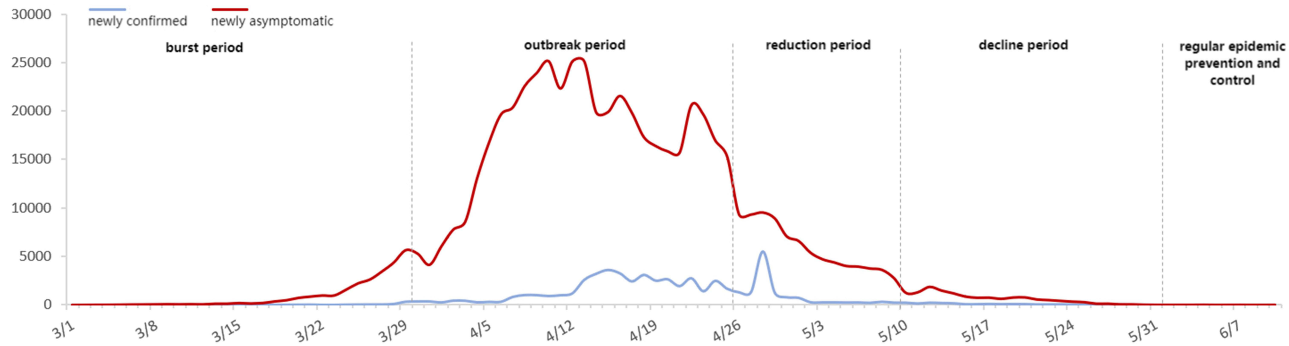


**Figure 2** Stages of development of the epidemic in Shanghai.

collected. This approach allowed for the comprehensive inclusion of data encompassing both hypertexts and topics, thereby enhancing the precision of retrieving demands information specific to the Shanghai region. A total of 15,607 microblogs were amassed, comprising user nicknames, posting times, and microblog content.

### Construction of Public Demands Dataset Based on ERNIE 3.0 Model

ERNIE 3.0 introduces large-scale knowledge graphs into pre-training models, reaching into the tens of billions for the first time. It puts forth a parallel pre-training method involving massive unsupervised text and large-scale knowledge graphs, termed Universal Knowledge-Text Prediction.[29] This innovative approach involves simultaneously inputting 50 million knowledge graph triples, obtained through a knowledge graph mining algorithm, and a 4TB large-scale corpus into the pre-training model for joint mask training. This process enhances information sharing between structured knowledge and unstructured text, significantly improving the model's ability to memorize and reason about knowledge.

In this study, ERNIE 3.0 is used to construct the public demand dataset. The data undergo initial cleaning to eliminate noise, including punctuation, special symbols, URLs, etc. Subsequently, the text is labeled for claim relevance classification. A labeled dataset of 3000 entries is used as the training set for the ERNIE 3.0 model. Texts containing specific help-related content are assigned as 1, while texts unrelated to assistance, such as venting emotions, providing help, making suggestions, etc., are labeled as 0. The labeled data are then input into the ERNIE 3.0 model, characterized by 12 layers, 768 hidden units, 12 heads, and 118M parameters. Following training, the model performs effectively, achieving an accuracy of 90.03% on the test set, an F1 value of 90.91%, and an AUC reaching 96.82%. Consequently, the public demand dataset consists of 8541 entries of public help data.

## Stage 3: Topic Mining for Public Demands Based on BERTopic Modeling

The BERTopic model is a topic mining model based on BERT that leverages a pre-trained deep learning model to extract text features, capture semantic information within the text, perform text clustering, and generate hot topics. The BERTopic model effectively addresses both the sparsity problem and static defects inherent in the LDA model when analyzing short texts. Notably, BERTopic exhibits superior capabilities in topic mining compared to LDA.

The main steps of public demands topic mining based on the BERTopic model are shown in Figure 3

The main steps include the following:

1. Convert each data in public demand dataset into word embedding using BERT.

2. Use the UMAP algorithm to reduce the dimensionality of the obtained embedding vectors to optimize the public demand clustering process.

3. Use density based clustering algorithm HDBSCAN to cluster and separate abnormal public demand data.

4. Use TF-IDF class based variant C-TF-IDF to extract public demand topic representations. It encapsulates all public demand data under the class, and then applies the TF-IDF method to identify the most important words in the class to represent the topic. Its calculation formula is shown in Equation (1).

$$W_{t,c} = tf_{t,c} \cdot \log\left(1 + \frac{A}{tf_t}\right) \tag{1}$$

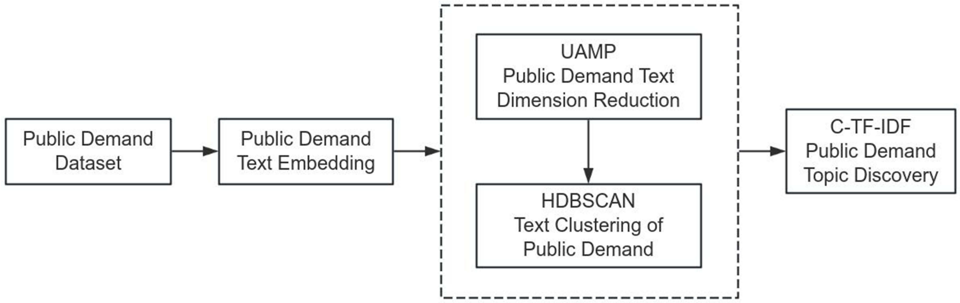


**Figure 3** Steps of public demands topic mining based on BERTopic.

The variables in the equation are defined as follows: $tf_{t,c}$ represents the frequency of occurrence of word t in category c, $tf_t$ represents the frequency of occurrence of word t in all categories, and A represents the average number of words in each category.

## Stage 4: Construction of Geographic Knowledge Graph of Public Demands Based on the UIE Model

The UIE model (Unified Structure Generation for Universal Information Extraction) has good generalization performance in tasks such as entity extraction, relationship extraction, event extraction, and sentiment analysis. The UIE model proposes a structured extraction language that represents the localization and association information in information extraction using a unified structure. It uses a prompt-based target information guidance mechanism to extract information on demand to control the extraction targets under specific tasks, scenarios and settings.

In this study, the geographical information in the public demand dataset is first annotated. Public demands often include the geographical locations of people in need of assistance. These geographical details can spatially reflect the situations requiring help, aiding rescue personnel in quickly identifying the concentrated areas of public demands. UIE can rapidly enhance model performance through small-sample training, annotating <District, street/Town, Community/Village> as entity triplets to create a training set of 300 public demand data containing geographical information. The previously obtained public demand dataset is input into the trained UIE model, resulting in 5812 public demand data containing geographical information, with details for each entity provided in Table 1.

The choice of "City district, street/Town, Community/Village" as three-level locations for entities effectively encompasses the primary entities of geographic information within the public demands. This three-level location classification not only aids managers in comprehending the extent of affected individuals in distinct areas but also pinpoints managerial challenges and resource limitations in various locations. Consequently, it serves as a foundation for resource allocation in community management and the dispatch of emergency materials.

# Results

## Topic Mining

Using the BERTopic model, topic mining is conducted on the public demand data with time information, resulting in a total of 24 topics. The topics are then arranged in descending order, with topic 0 representing the public demand topic with the highest percentage. Subsequently, these topics undergo further consolidation based on a hierarchical structure map. The hierarchical structure map of the topics is illustrated in Figure 4.

**Table 1** Entity Information

| Entity | District | Streets/Towns | Community/Village |
|---|---|---|---|
| Number | 5812 | 4510 | 2424 |

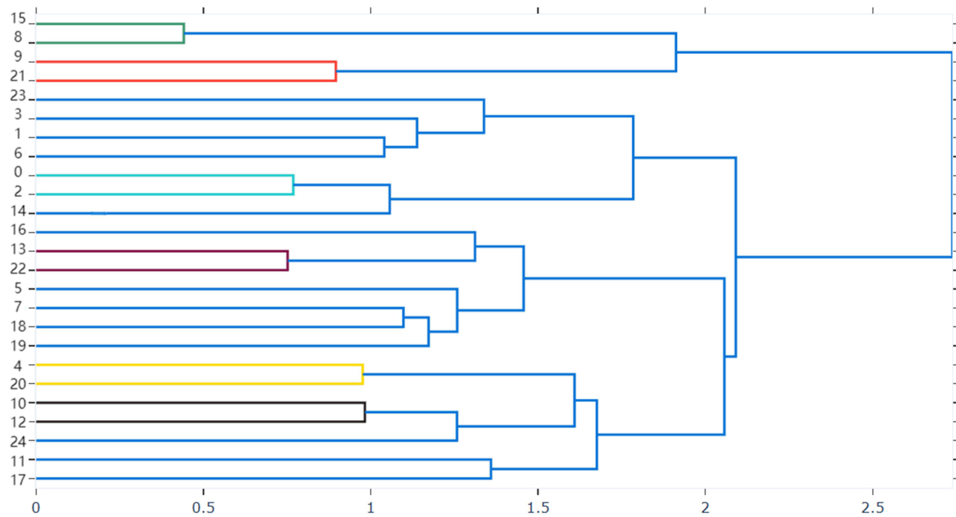


**Figure 4** The hierarchical structure map of the topics.

The hierarchical structure map can help understand the potential hierarchical structure of topics and reduce the number of topics. The topics were summarized based on the keywords in the hierarchical structure map, and similar topics were merged to form core topics. Finally, 7 core topics of public demands were obtained, as detailed in Table 2. The three most concentrated topics are supplies demands, medical demands, and epidemic prevention measures.

**Table 2** Public Demands Topics

| Core Topics | Topic Number | Topics |
|---|---|---|
| 1. Medical demands | Topic 0 | Diagnosis and treatment |
| | Topic 18 | Medical treatment for the elderly |
| | Topic 19 | Medical treatment for Children |
| | Topic 24 | Medical treatment channels |
| 2. Supplies demands | Topic 1 | Supplies distribution |
| | Topic 3 | Food needs |
| | Topic 4 | Maternal and infant needs |
| | Topic 8 | Group Purchasing |
| | Topic 9 | Supplies purchase |
| | Topic 10 | Medicine needs |
| 3. Epidemic prevention measures | Topic 2 | Community management |
| | Topic 6 | Commercial and residential user needs |
| | Topic 5 | Shelter construction. |
| 4. Transportation demands | Topic 7 | Retention |
| | Topic 13 | Travel |
| | Topic 14 | Return home |

(*Continued*)

**Table 2** (Continued).

| Core Topics | Topic Number | Topics |
|---|---|---|
| 5. Delivery demands | Topic 12 | Errands |
| | Topic 20 | Logistic |
| 6. Isolation measures | Topic 16 | Isolation location |
| | Topic 22 | Isolation Environment |
| 7. Pet demands | Topic 11 | Pet related |

A sorting analysis of the number of these three hot topics by districts found that in 50% of districts, supplies demands are the most urgent public demands.

Topic #1, "Medical demands" include public demands related to "Diagnosis and treatment", "Medical treatment for the elderly", "Medical treatment for children", and "Medical treatment channels". It can be seen from the topic words that "Diagnosis and treatment" mainly refers to the medical needs of patients diagnosed with COVID-19. "Medical treatment for the elderly" is mainly for hemodialysis and chemotherapy needs of the elderly at home. And "Medical treatment for children" focuses more on the isolation and treatment of infants and young children. "Medical treatment channels" mainly refers to the medical treatment process and hospital admissions.

Topic #2, "Supplies demands" include 'Supplies distribution', 'Food needs', 'Maternal and infant needs', 'Group purchasing', 'Supplies purchase' and 'Medicine needs'. The supplies most needed by the public are food, maternal and infant products, and medicines. Supplies are mainly obtained through government distribution, online group purchases, and offline purchases. These three methods have problems such as short supply, difficulty in distribution, and operational barriers.

Topic #3, "Epidemic prevention measures" include "Community management", "Commercial and residential user needs" and "Shelter construction". Some epidemic prevention measures taken by local governments affected the normal lives of residents in the community, thus generating public demands. Commercial and residential users mainly refer to residents who rent in commercial and residential buildings. Due to unclear rights and responsibilities in the management of commercial and residential buildings, it is difficult to receive timely feedback on the basic needs of residents living in commercial and residential buildings after the lockdown. The construction of shelters is mainly a matter of site selection. The new shelters are chosen to occupy primary schools or be built near residential areas, causing dissatisfaction among parents and nearby residents.

Topic #4, "Transportation demands" include three main demands: "Detain", "Travel" and "Return home". Flight cancellations, train suspensions, community blockades and other measures have caused trouble to the public who need to travel. Some people were stranded at the airport or train station, and some people are unable to return to their communities after going out.

Topic #5, "Delivery demands" include "Errands" and "Logistics". Errands are people who buy needed goods for others and have them delivered to their door in the same city. Logistics mainly refers to the distribution needs after online shopping or transactions in other provinces.

Topic #6, "Isolation measures" include isolation location and isolation environment. Some people are being quarantined in hotels, and they are concerned about the cost and duration of quarantine. Shelter isolation has some environmental problems, such as sanitary conditions, infrastructure, treatment conditions.

Topic #7, "Pet demands" mainly concern the placement of pets at home after owners are quarantined, and the purchase of pet food after logistics is stopped.

## Thematic Evolution of the Time Dimension

According to the content and percentage of public demand topics, representative topics selected for evolution analysis in each of the seven core topics are TOPIC 0, 1, 2, 7, 10, 12, 11, and 16, shown in Figure 5.

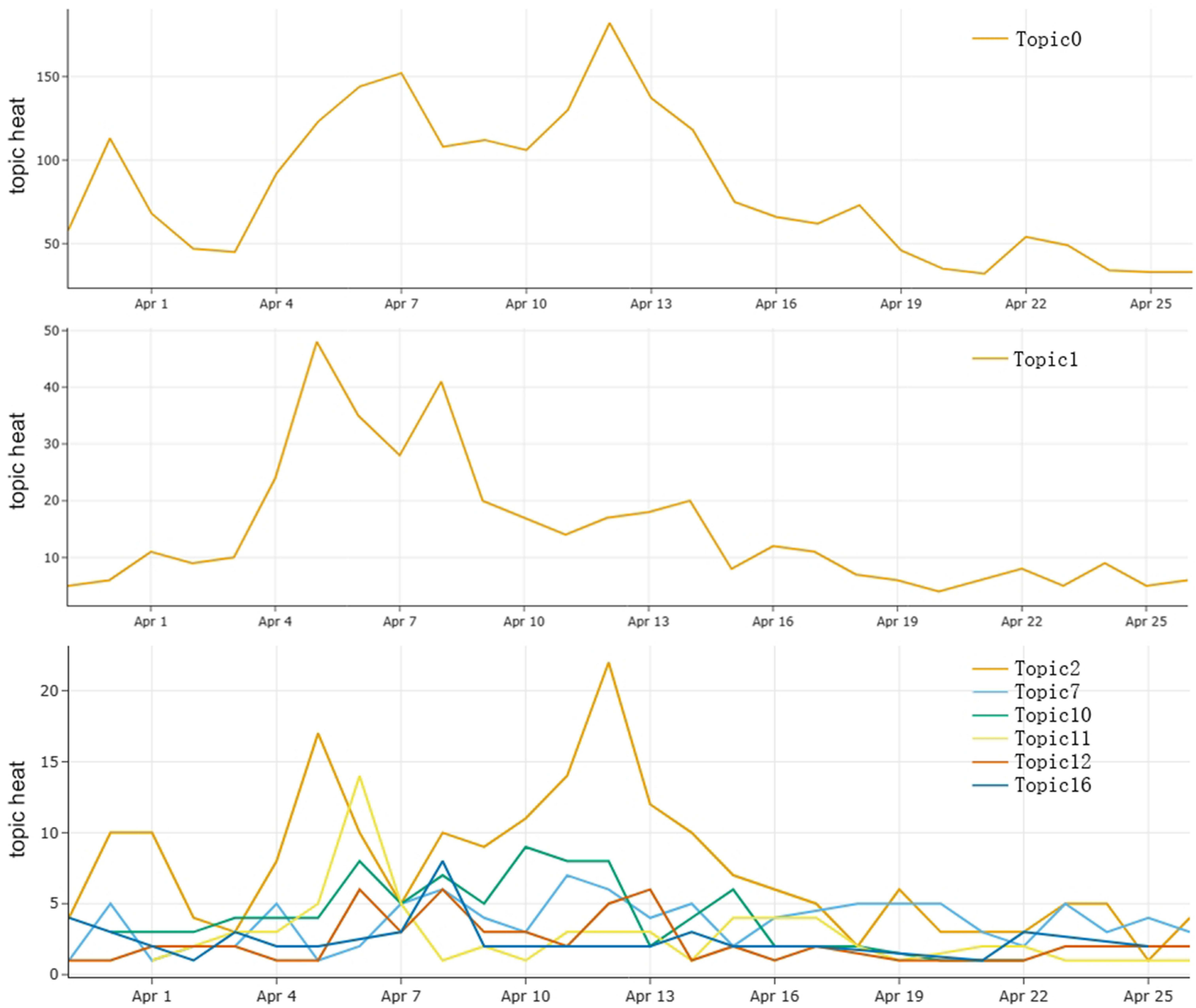


**Figure 5** Evolution of public demand topics.

Notably, TOPIC 0 and TOPIC 1, as the two largest topics, have a different range of topic heat compared to the other topics, and they are explained separately.

The diagnosis and treatment topic reached its peak on April 12th, followed by a rapid decline. Figure 5 indicates a corresponding peak in confirmed asymptomatic infections around April 12th. Notably, the trend in the diagnosis and treatment topic aligns with the overall epidemic trend in Shanghai.

The second most popular topic is supply distribution, peaking on April 5, preceding the diagnosis and treatment topic. Subsequently, a decline commenced after April 8. The trajectory of this topic is intricately linked to government measures. Initially, during the early stages of the lockdown, residents had ample supplies at home, resulting in fewer demands for distribution. However, with the consumption of supplies and the unknown duration of the lockdown, residents who have not stocked up on supplies will have a need for supplies and fear of running out of food, leading to a significant increase in demands for supply distribution. After paying attention to the relevant public opinion, the government took measures to meet the public's supplies demands, and the demands began to decline.

Among the other topics, the community management topic gained substantial popularity in the early stages due to the lockdown. Its peak occurred between April 4th and 7th, mirroring the trend observed in the pet demands topic. Following this peak, pet demands rapidly declined, while the community management topic experienced another surge, reaching its zenith on April 12th. The subsequent evolution closely resembled that of the diagnosis and treatment topic.

The sudden lockdown accentuated challenges in community management, including environmental disinfection, nucleic acid arrangement, and attitudes toward pet handling. This resulted in a surge of public demands. As the lockdown persisted and confirmed cases increased, conflicts between some community managers and residents deepened. On April 12th, an online exposure of a recorded conversation between elderly individuals and community managers stirred significant public opinion. In response, community managers began acknowledging and addressing public needs, fostering a growing understanding of the challenges they faced. Consequently, the popularity of the community management topic gradually waned.

The evolutionary trend of the other topics followed a relatively smooth trajectory, peaking in the April 4–13 period. In contrast to the other topics, the retention topic did not experience a rapid decline in intensity in the later period, indicating that the retention problem has not been adequately addressed.

Overall, diagnosis and treatment are the most popular topic throughout the whole period, followed by supplies distribution. Therefore, demands for medical treatment and supplies play a major role during the epidemic lockdown period. In addition, the most popular topic before April 16 was community management, and after that, retention and community management were equally popular. This shows that the demand for prevention and control measures was relatively high in the early and mid-term, and the proportion of transportation demands increased in the later period. Delivery demands, isolation measures and pet demands did not fluctuate much during the entire time period, and their proportions were low.

## Visualization of Spatial Information

A statistical chart based on the open data of the Shanghai Municipal Health Commission[30] depicting the number of confirmed cases in 16 districts of Shanghai from March 30 to April 29 is presented in Figure 6. Pudong New District emerges as the most severely affected, recording a total of 13,975 confirmed cases, while Fengxian District is the least affected, with a total of 207 confirmed cases. Additionally, topic mining was performed on the data in each district, and the results are summarized in Table 3.

Upon analyzing the correlation between the number of confirmed cases, post count, and popular topics in each district, a direct proportionality between the number of confirmed cases and posts was observed in most districts. Pudong New Area, with the highest number of confirmed cases, also led in the count of posts. Conversely, districts like Fengxian, Jinshan, and Chongming, with fewer confirmed cases, exhibited lower post counts. While our previous analysis identified the diagnosis and treatment topic as the most popular overall, core topics reveal variations. In 9 of the 16 districts, supplies demands emerged as the leading topic, followed by epidemic prevention measures in 4 districts, and diagnosis and treatment in 3 districts. Putuo District and Baoshan District diverged from others, showing relatively fewer confirmed cases but a higher number of posts. Notably, public demands focused on epidemic prevention measures and supply demands, highlighting their prominence compared to diagnosis and treatment. Yangpu District, despite having a lower number of confirmed cases, displayed strong medical demands.

In order to further explore the spatial dimension information in the data, the triples extracted from the UIE model were used to construct a geographical knowledge graph. Each node represents an entity, and the edges between entities represent the relationship between them. From such visual analysis, geographic information on public demands can be quickly obtained,

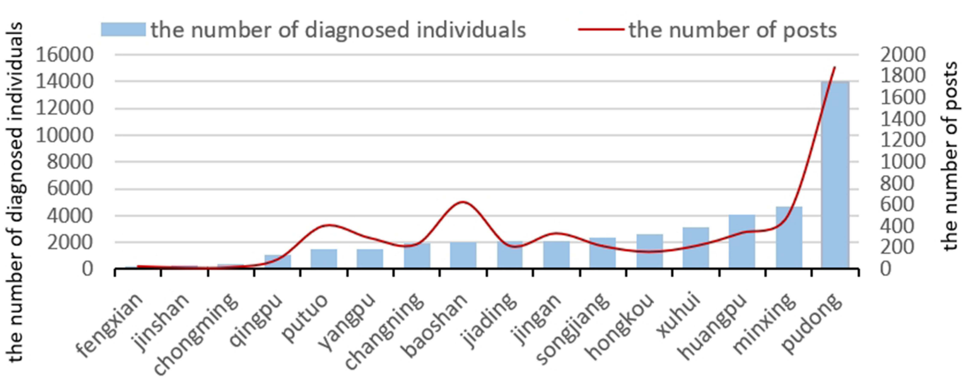


**Figure 6** Number of posts and number of confirmed cases in each district.

**Table 3** Topics of Most Concern in Each District

| Districts | Fengxian District | Jinshan District | Chongming District | Qingpu District |
|---|---|---|---|---|
| **Demand Topics** | Supplies demands | Supplies demands | Supplies demands | Supplies demands |
| **Districts** | Jiading District | Jing'an District | Songjiang District | Hongkou District |
| **Demand Topics** | Medical demands | Epidemic prevention measures | Supplies demands | Epidemic prevention measures |
| **Districts** | Putuo District | Yangpu District | Changning District | Baoshan District |
| **Demand Topics** | Epidemic prevention measures | Medical demands | Epidemic prevention measures | Supplies demands |
| **Districts** | Xuhui District | Huangpu District | Minxing District | Pudong New Area |
| **Demand Topics** | Supplies demands | Supplies demands | Supplies demands | Medical demands |

and areas with serious problems can be located. The classification of geographical information can help guide the formulation and implementation of government policies at different levels,[31] and provide a basis for public health emergency material dispatch.

# Discussion

## Implications

It is well known that one of the challenges in generating emergency plans for public health emergencies is how to quickly and accurately generate an effective plan for the development of an outbreak so that government departments, health systems, and hospitals can respond in time to protect the health of the public.

This study analyzes online public demands from two dimensions: static space and dynamic time. Public demands during the Shanghai epidemic are divided into seven categories: medical demands, supplies demands, epidemic prevention measures, transportation, delivery demands, isolation measures and pet demands. These delineated categories serve as valuable insights for government in public health emergency decision-making and management, enabling them to effectively meet public demands and allocate public health emergency resources.

This study reveals evolving trends in public demand during health emergencies. Research shows that supplies demands, medical demands and epidemic prevention measures, which account for a large proportion of public demands, show an evolutionary trend of first increasing and then decreasing. Interestingly, transportation demand increased in the later period, contrary to the downward trend of other demand categories. The evolution of demand topics is mainly affected by the progress of the epidemic, online public opinion and government decisions. The method of constructing the evolutionary path of topics based on time series enables the classification of public demands to adapt to different stages of public health emergencies and helps decision-makers deploy public health emergency management by considering longer time periods.

This study explores the construction of a geographical knowledge graph of public demands based on the UIE model. This geographical knowledge graph provides local government with a comprehensive understanding of the situation and public demands across different areas, offering valuable insights for public health emergency management departments to swiftly identify regions with significant public demands.

# Limitations

Spatial analysis relied solely on geographic name information extracted from SINA Weibo, overlooking the inclusion of user geographic coordinate data. While some scholars argue that geographic coordinate data may be unavailable or inaccurate,[32] integrating both spatial information sources could potentially enhance the accuracy of localization results.

# Conclusion

In public health emergencies, public demands act as weathervanes, responsive to public policies[33] and signaling when adjustments are needed[34] in government policies. The government's ability to address public demands is a central concern in modern governance capacity and administrative system construction. China is increasingly turning to modern information technology as a novel approach for governmental responses to public demands.[35]

This study proposes a spatio-temporal evolution analysis method based on the EBU models for analyzing public demands during health emergencies. This method which integrated three large language models (ERNIE, BERTopic, UIE) is a novel approach in responding to health emergencies. It streamlines the labeling and training process, requiring only a small sample for pre-training and fine-tuning, resulting in a more effective model. The study's focus on the spatio-temporal evolution of public demands provides a comprehensive understanding of the dynamics during health emergencies. This dual focus is a fresh perspective that can lead to more nuanced policy-making and response strategies. Consequently, this study extends the scope and depth of research on public health emergency management, enriching subject categories and research methods in the context of public health emergencies. The use of social media data underscores its potential as a valuable tool for analyzing public demands.

Furthermore, this study presents an innovative contribution at the intersection of risk management and technology by applying cutting-edge artificial intelligence (AI) techniques to the real-time analysis of social media data, thereby enriching information sources for public health policymaking. This represents a significant advancement in the modernization of public health emergency management, enabling governments and relevant departments to harness the power of social media data more effectively.

## Data Sharing Statement

Due to privacy restrictions, the data presented in this study are available upon request from the lead author (Yuan Zhang), upon reasonable request.

## Ethics Approval

The authors confirm that this study does not involve human participants, case studies, human samples, or animal samples, and does not present any ethical risks or challenges related to life and health, ecological environment, public order, or sustainable development. Therefore, ethical review is not required for this study under Chinese law. The requirements for academic ethical review in China can be accessed through the website https://www.gov.cn/zhengce/zhengceku/202310/content_6908045.htm.

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## Disclosure

The authors report no conflicts of interest in this work.

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