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# Misinformation dissemination on social media: key research themes and evolutionary paths between 2013 and 2023

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With the rapid development of information technology, the proliferation of misinformation has become a global security challenge. Examining the dissemination and governance of misinformation on social media is both challenging and significant. In this study, we review the research progress regarding the spread of misinformation on social media, analyzing a total of 3283 relevant articles indexed in the Web of Science from 2013 to 2023. First, we discuss the concept of misinformation and the data acquisition platforms used in misinformation research. Next, we propose a new research framework that integrates complex networks, community segmentation, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and the Analytic Hierarchy Process (AHP) method, revealing the thematic evolution of misinformation dissemination research over the past decade. Subsequently, we comprehensively discuss several research hotspots, including health misinformation, political misinformation, governance methods for misinformation, and future trends. The findings of this study may provide valuable insights for future research on misinformation and serve as references for the formulation of effective governance strategies.

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## Introduction

Social media has become an effective channel of information acquisition and communication in the digital era (Ulusan and Özejder, 2024); however, it is also an significant place for the generation and dissemination of misinformation (Lu et al., 2019). Misinformation refers to information that deviates from the true state of objective things and certain measurement standards (Loftus and Hoffman, 1989). In recent years, a substantial amount of misinformation, such as fake news, rumors, and malicious messages, has emerged on the Internet. Contributing factors to the breeding and spread of misinformation include a lack of factual experience, emotional fluctuations, and the formation of prejudices. The openness and anonymity of social media facilitate users' sharing and exchanging of information, but they also render users vulnerable to unlawful behaviors. The wide dissemination of misinformation has serious negative impacts on individuals and society; for instance, in 2013, the Associated Press was hacked and tweeted fake news about an "explosion that injured Barack Obama", which subsequently triggered sharp turbulence in the stock market.

The spread of misinformation alters how people comprehend and respond to true information, hindering their ability to distinguish right from wrong. As the number of social media users worldwide continues to rise, concerns about the generation and dissemination of misinformation are growing as dependence on social media are escalating, particularly as reliance on social media grows. Notably, 56% of users express concerns about the accuracy of the information they encounter, and 40% worry that social media platforms contain misinformation (Newman et al., 2021). More than 70% of people across 19 countries and regions in North America, Europe, and the Asia-Pacific believe that the spread of online misinformation has become one of the "major threats" in today's world. The proliferation of misinformation on social media has raised significant concerns among governments and international organizations. To tackle this challenging issue, the European Commission published a Code of Conduct against misinformation in 2018. This initiative is the world's first industry-wide effort to combat misinformation through self-regulation. The PolitiFact website categorizes a significant amount of social media information into six distinct levels based on credibility. Meanwhile, the International Fact-Checking Network (IFCN) has established a fact-checking community to advance the institutionalization of governance in cyberspace.

The widespread dissemination of misinformation on social media can lead to psychological imbalances, behavioral disorders, economic dislocations, and social disorders at the societal level. Therefore, studying the propagation mechanisms of misinformation and accurately detecting and efficiently intervening its spread on social media is of great significance. Researchers from various disciplines have conducted extensive research focusing on misinformation (Bodaghi et al., 2023; Caled and Silva, 2022; El Mikati et al., 2023; Hangloo and Arora, 2022). For instance, Hangloo and Arora (2022) conducted a comprehensive review of technologies aimed at combating misinformation on social media. Based on recent literature, El Mikati et al. (2023) examined the implications of health misinformation, highlighting the consistencies and differences among various forms of misinformation. Caled and Silva (2022) explored the mechanism behind the generation and dissemination of misinformation in social networks and proposed several strategies for addressing it. As noted by Bodaghi et al. (2023), misinformation can be classified as intentional or unintentional, and they have suggested effective strategies for detecting, verifying, and mitigating both types.

Existing review studies primarily focus on the specific content and technology of misinformation management, overlooking a

comprehensive analysis of research trends in this field. Topic evolution analysis is a methodology employed to examine the changing patterns and development of specific themes or subjects over time. This analysis employs textual data elements such as keywords, thematic structures, and sentiment orientations to reveal temporal variations in subject trajectories. It also evaluates the impact of critical events and explores the dynamic progression of relevant factors. Consequently, this study aims to explore the topic evolution concerning misinformation dissemination within social networks. This study utilized a scoping review framework combined with bibliometric analysis to systematically elucidate the evolution of the knowledge structure in the field of social media misinformation research. Specifically, this study aims to review recent research on misinformation dissemination on social media by analyzing the related recent articles retrieved from the Core Database of the Web of Science. To systematically investigate the progress in relevant research, we introduce a novel framework integrating time slicing, community detection algorithms, AHP, and TOPSIS. This approach provides a comprehensive perspective, enhancing our understanding of key research topics and developmental trends.

The rest of this paper is organized as follows. First, we introduce the materials and propose an integrated research framework. Next, based on a total of 3283 articles related to misinformation published over the past decade, we conduct a systematic investigation of the conception and definition of misinformation, the data acquisition platforms used for misinformation research, key research themes and their evolutionary pathways, as well as methods for governing misinformation. Subsequently, we discuss some limitations and future trends. Finally, we present conclusions to address the initial four questions.

## Materials and methods

In this study, misinformation is defined as all forms of false information (Darwish et al., 2023; Jung et al., 2020; Pulido Rodriguez et al., 2020; Vosoughi et al., 2018; Wang et al., 2019). This paper focuses on social media misinformation and utilizes the Web of Science Core Database as the data source, covering the period from January 1, 2013, to December 31, 2023. Different from traditional literature review, this study provides an intuitive visual demonstration of ten years of research on misinformation, utilizing a visual framework for topic evolution. Our aim is to review the research progress, identify key issues and hotspots, assess mainstream research methods, and analyse future trends in the field of misinformation by addressing the following questions:

**RQ 1.** What are the relevant terms and concepts involved in the field of misinformation research, and which types of misinformation have been studied more extensively?

**RQ 2.** Which are the mainstream social media platforms that are mostly utilized in the misinformation-related literature?

**RQ 3.** Based on the misinformation-related literature in the past decade, what are the evolutions in research hotspots and key research issues?

**RQ 4.** What are the popular research methods employed by scholars to conduct in-depth studies on the governance of misinformation spread on social media platforms?

Figure 1 illustrates the research framework, which is composed of six stages. The first stage involves data retrieval; this study collects relevant published literature based on keywords related to misinformation dissemination and social media. In the second stage, noisy keywords are pre-processed. The third stage involves constructing a co-keyword network segmented by time slices. The fourth stage entails initial community detection within the constructed keyword co-occurrence network, followed by the

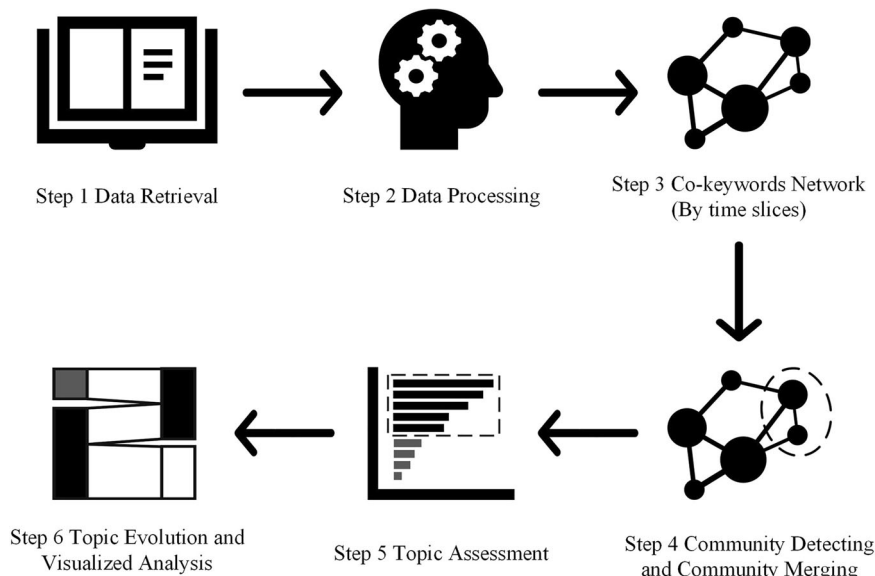


Fig. 1 An overview of the research framework.

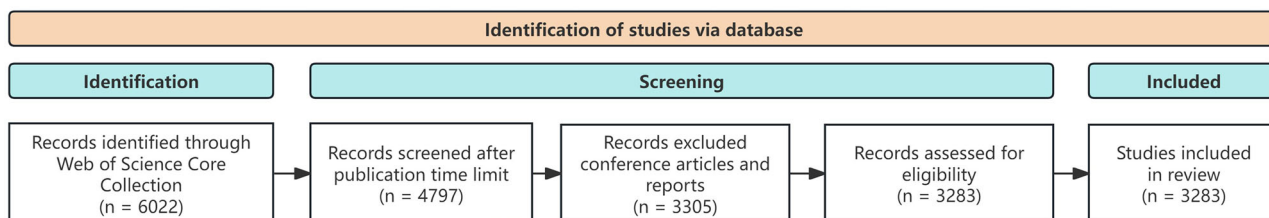


Fig. 2 Literature screening flow chart of Web of Science Core Collections.

merging of weak communities based on path length information. In the fifth stage, the TOPSIS method is applied to evaluate the importance of nodes in the co-keyword network and to identify research hotspots. Finally, the sixth stage utilizes visualization techniques to present the research hotspots and future trends in misinformation within social media.

**Data retrieval.** This study aims to conduct a literature review on the dissemination of misinformation in social media, focusing on the evolution of research themes. Inspired by previous studies (Chen et al., 2023), the keyword search strategy is defined as: “TS = ((misinformation OR disinformation OR “fake news” OR “false information” OR rumo\* OR “misleading information”) AND (“social media” OR “social network”) AND (spread\* OR shar\* OR diffuse\* OR disseminated\* OR propagate\* OR broadcast\* OR circulate\*))”. The data used in this study are sourced from the Web of Science Core Collection, a comprehensive and multidisciplinary citation index database. This database encompasses various disciplines, including the natural sciences, social sciences, engineering, and technology, offering a valuable resource for interdisciplinary research. We searched for relevant articles in the Web of Science Core Database, limiting the date range from January 1, 2013 to December 31, 2023. This study specifically excluded conference articles and research reports, ultimately including 3283 journal papers that met thematic and methodological criteria. Figure 2 illustrates the flow chart of literature screening process, where n denotes the number of literature, and a total of 7714 keywords were obtained. A preliminary statistical analysis for these articles is displayed in Fig. 3, indicating a year-on-year increase in related publications, with particularly explosive growth observed since 2018.

Misinformation research has emerged as a significant and dynamic topic within the field of information dissemination on social media.

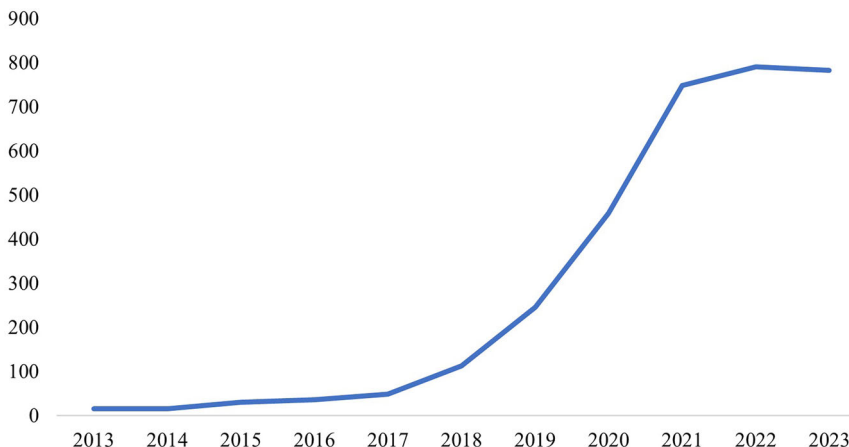
**Construction of co-keyword network.** To explore the research hotspots in different periods, we construct keyword co-occurrence networks based on the selected literature. To effectively extract keywords, data preprocessing is performed with the aid of the software tool ITGinsight (Wang et al., 2022). More specially, the detailed process is outlined in Table 1. In addition, some noisy keywords with a word frequency of less than 2 are removed in each time slice, facilitating the construction of co-keyword networks.

As shown in Fig. 3, the number of publications between 2013 and 2018 is relatively small, but there has been explosive growth since then. To analyze this trend, we extracted keywords from the literature from 2013 to 2018 to construct a keyword co-occurrence network. For the period from 2019 to 2023, we created four additional keyword co-occurrence networks, each corresponding to a specific yearly time slice. Table 2 displays the basic topological characteristics of these six keyword co-occurrence networks, where nodes and edges represent keywords and their co-occurrence relationships, respectively, and weights indicate the intensity of co-occurrence between keyword pairs.

The co-occurrence cosine index (Huang et al., 2019) can be considered as the co-occurrence intensity among keywords, which can be calculated as,

$$\text{cosine}(a, b) = \frac{F(a, b)}{\sqrt{F(a) \times F(b)}} \tag{1}$$

where F(a) and F(b) are the frequency of occurrence of keyword a



**Fig. 3** Changes in the number of literatures related to misinformation spread (2013-2023).

**Table 1** Examples of data preprocessing.

Data preprocess	Example
Remove some symbolics such as “()”, “-” et al.	“Fact-checking” is changed to “Fact checking”
Merge singular and plural forms	“Social networking”, “Social networks” and “Social network” are replaced with “Social network”
Combine synonyms	“Health related misinformation” and “Health misinformation” are merged into “Health misinformation”

**Table 2** Basic topological characteristics of co-keyword networks in six time periods.

Period	Nodes	Edges	Average Degree	Average Weighted Degree
2013-2018	144	619	8.597	0.755
2019	140	627	8.957	0.732
2020	250	1717	13.736	0.681
2021	411	3603	17.533	0.639
2022	472	3840	16.271	0.648
2023	406	3558	17.527	0.656

and keyword b in the same chronological literature, respectively.  $F(a, b)$  is the number of times keyword a and keyword b co-occurrence. Figure 4 gives the keyword co-occurrence network for the period from 2013 to 2018. In this network, the size of each node reflects the volume of literature related to the specific key term, and the edges connecting the nodes indicate co-occurrences of these terms in the literature (Shang et al., 2024). For instance, the edge connecting “social media” and “misinformation” in Fig. 4 indicates their co-occurrence as keywords within the same research paper (Radhakrishnan et al., 2017). It is evident that topics such as social media and infection sources have attracted significant attention and have been the focus of ongoing research in the field of misinformation. To save space, the other four keyword co-occurrence networks are omitted here.

**Identification of key research themes.** Based on the obtained co-keyword networks, we propose a new algorithm for identifying important research topics related to misinformation dissemination. This algorithm integrates a community detection algorithm with AHP and the TOPSIS method to assess the influence of nodes and thus identify key nodes in social networks more effectively (Liu et al., 2015). The proposed algorithm comprises three phases.

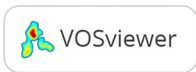
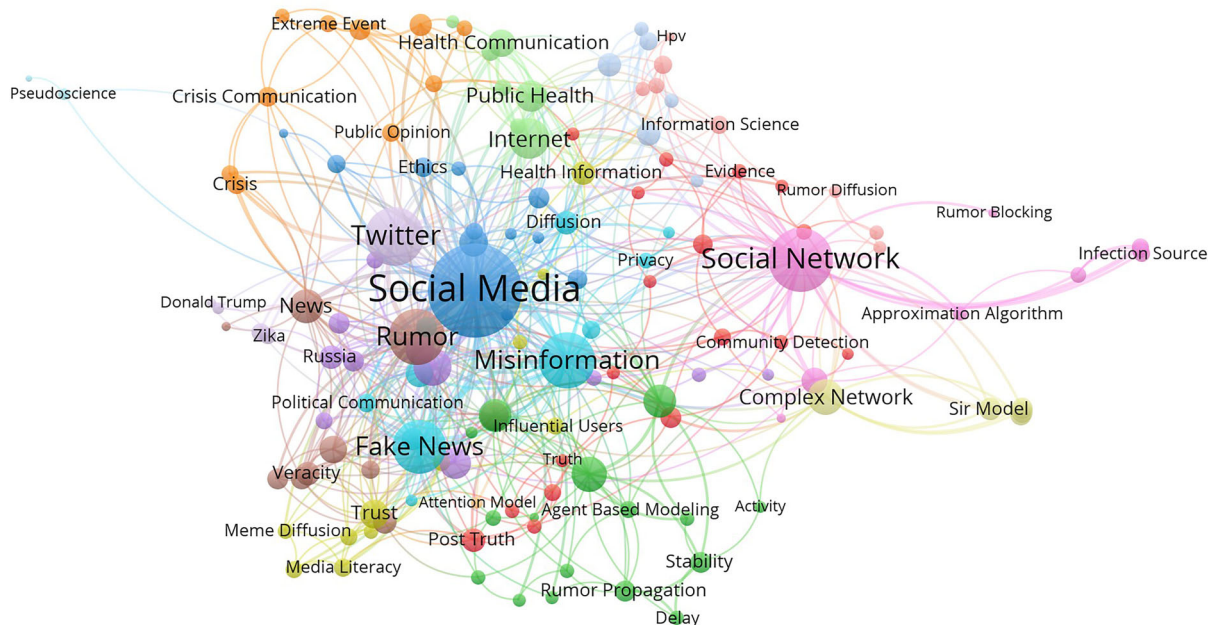
**Phase 1: Community division.** The classic Louvain algorithm (Blondel et al., 2008) is employed to get the community partition for the constructed keyword co-occurrence networks.

**Phase 2: Community consolidation.** A new merging strategy is designed to optimize the initial community division. The pseudo-code of the proposed algorithm is shown in Algorithm 1.

**Phase 3: Topic identification.** With the aid of the AHP and TOPSIS method, the core keywords and key research themes are obtained according to several topological indicators of co-keyword networks.

**Algorithm 1. Identification of key research themes**

**Input:** Co-keyword Network  $G = (V, E)$ ,  $|V(G)| = N$   
 Using the Louvain algorithm to get the initial community structure  $C = \{C_1, C_2, \dots, C_p\}$   
 Generate weak communities  $C_W = \{C_{W1}, C_{W2}, \dots, C_{Wx}\}$  based on the community scale  
 Set  $j \leftarrow 1$   
**while**  $C_W \neq \emptyset$  **do**  
     Search for the nearest weak community  $C_{Wk}$  of  $C_{Wj}$   
      $C'_{Wj} \leftarrow C_{Wj} \cup C_{Wk}$   
     **if**  $Q'_{C'_{Wj}} < 0.4$  **then**  
          $C'_W \leftarrow \{C_W - C_{Wk} - C_{Wj}\} \cup C'_{Wj}$   
     **end**  
      $j \leftarrow j + 1$   
**end**  
 Obtain an optimized community structure  $C_M = \{C_1, C_2, \dots, C_{p1}\}$   
 Calculate the weights of the WDC, WBC, WCC, and WEC indicators using (2)  
 Set  $RT \leftarrow \emptyset$   
**for**  $k = 1$  to  $p_1$  **do**  
     Construct the normalized attribute matrix for the community  $C_k$   
     Determine the positive  $X^*$  and negative ideal object  $X^-$   
     Calculate the close degree to the ideal object for each keyword  
      $RT_k = \{\text{top 5 keywords in the community } C_k\}$



**Fig. 4** An example of co-keyword network (2013 to 2018).

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RT ← RT ∪ RTk
end
```

**return** Key research themes list RT

Modularity is used to assess the performance of community division. A larger value of modularity means that the community structure is more accurately detected. For real networks, the modularity value usually ranges from 0.3 to 0.7 (Blondel et al., 2008). Based on the algorithm as described above, we perform the community division for the five keyword co-occurrence networks, where some weak communities with modularity values less than 0.4 are merged. Then, according to the AHP method, the largest eigenvalue is obtained as  $\lambda_{\max} = \sum_{s=1}^4 \frac{d_s}{4w_s} \approx 4$  and  $D = (d_s)_{4 \times 1} = C \times \bar{W}$ ,  $p_{cl} = \frac{\lambda_{\max} - 4}{4 - 1} = 0$ , which indicates that the complete consistency is satisfied identically. Finally, the weighting coefficients of four indicators are computed as  $W^T = [0.0467, 0.1125, 0.4204, 0.4204]$ .

$$C = (c_{st})_{7 \times 4} = \begin{bmatrix} & WDC & WCC & WBC & WEC & M & W & \bar{W} \\ WDC & 1 & 9^{-\frac{2}{3}} & 9^{-1} & 9^{-1} & 0.0051 & 0.2676 & 0.0467 \\ WCC & 9^{\frac{2}{3}} & 1 & 9^{-\frac{1}{3}} & 9^{-\frac{1}{3}} & 0.1724 & 0.6444 & 0.1125 \\ WBC & 9 & 9^{\frac{1}{3}} & 1 & 1 & 33.635 & 2.4082 & 0.4204 \\ WEC & 9 & 9^{\frac{1}{3}} & 1 & 1 & 33.635 & 2.4082 & 0.4204 \end{bmatrix} \quad (2)$$

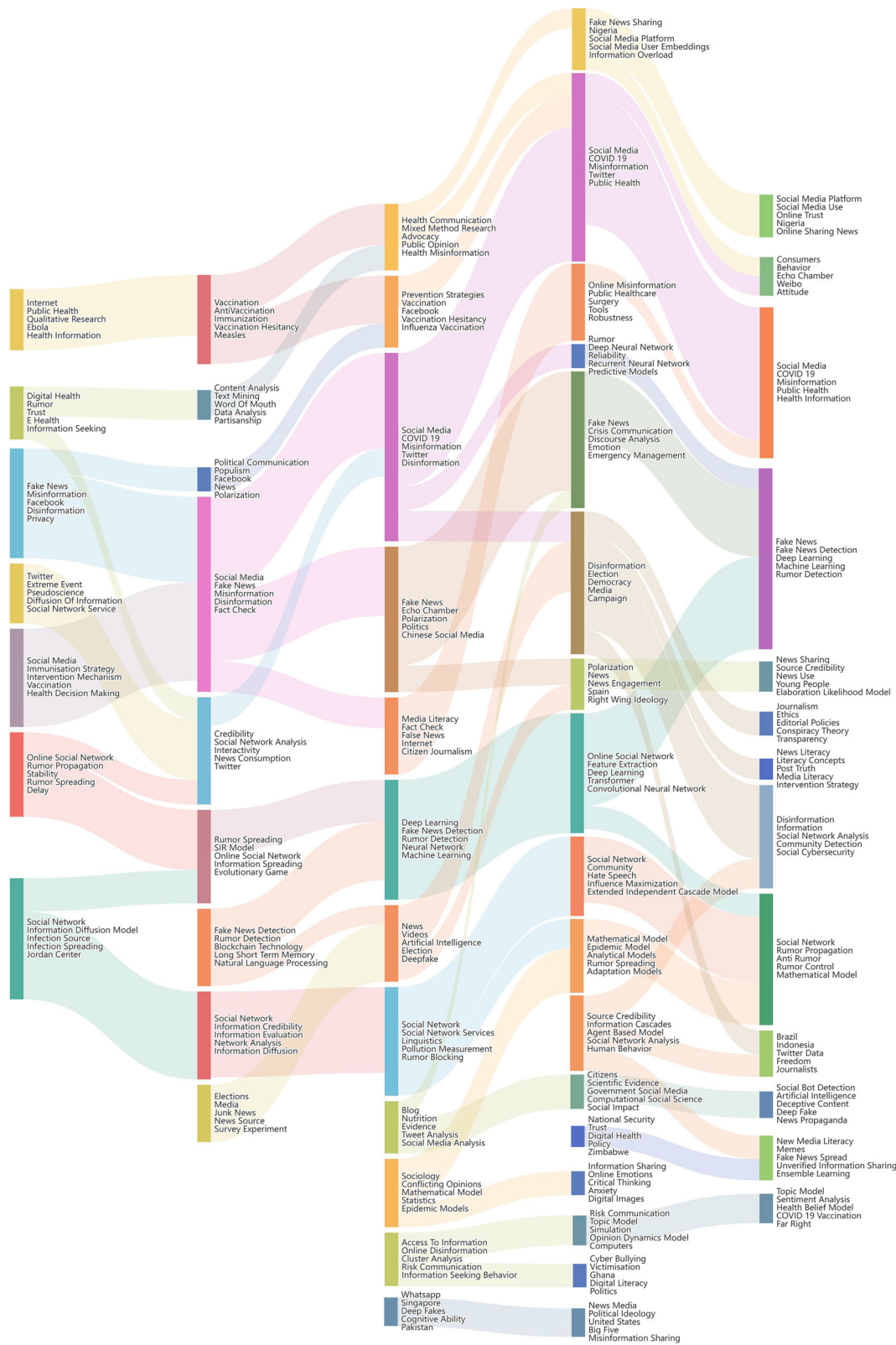
The community detection results for the five keyword co-occurrence networks are presented in Table 3. Following this, we can calculate the importance of keywords within each community using the obtained weighting coefficients of four different indicators, allowing us to identify the core keywords in each community. From this analysis, we can derive the key themes in misinformation dissemination research from 2013 to 2023.

**Visualization of research theme evolution.** Misinformation dissemination on social media is a significant cross-disciplinary research issue that has garnered much attention from scholars

Period	Modularity	Number of communities
2013-2018	0.5584	9
2019	0.5655	9
2020	0.4991	12
2021	0.4950	17
2022	0.5449	19
2023	0.4820	12

over the past decade. In this subsection, we aim to explore the evolution of research themes in this field through visualization tools. For this purpose, we utilize the cosine similarity algorithm (Patra et al., 2023) to calculate the similarity of topics within adjacent time windows, where a higher cosine value indicates a stronger correlation. Additionally, the Sankey diagram serves as an effective tool for visualizing the dynamic interplay and shifts between various topics over time. In addition, Sankey chart visually depicts the number and relative proportion of topics through the width of nodes and connecting lines. This intuitive representation highlights the size and proportion of flow between different topics, further aiding our understanding the importance and evolutionary trends of these topics.

Figure 5 reveals the evolutionary relationship of misinformation research on social media over the past decade from left to right. It is observed that the keywords within each topic exhibit diverse characteristics as the scope of misinformation research expands. The emergence of new topics or keywords reflects the change in the issues that scholars are focusing on. Furthermore, the ongoing splitting and merging of research topics have enhanced the richness and maturity of misinformation studies. More detailed findings and visual representations of topic evolution will be presented in the following section.



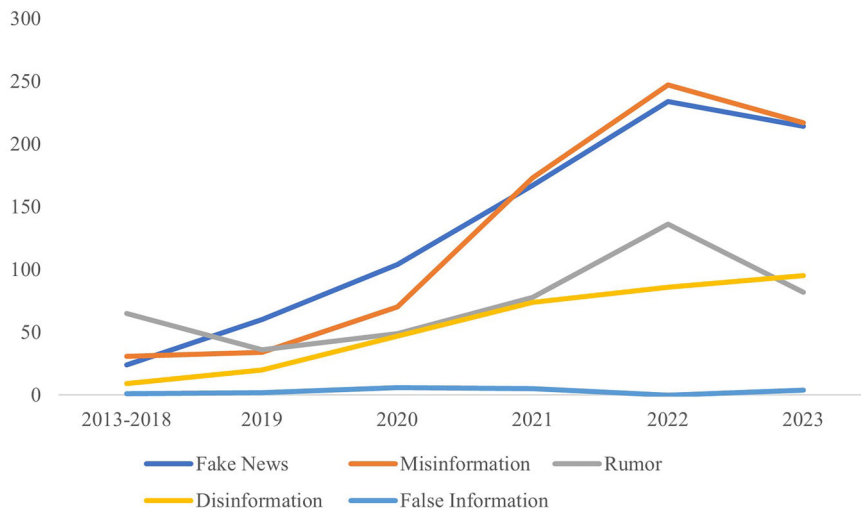
**Fig. 5** Topics evolution of misinformation dissemination research between 2013 and 2023.

**Results and analysis**

Based on the above method, this section systematically analyzes the evolution of key research themes in the field of misinformation dissemination on social media. Additionally, it addresses the initial four questions: the definition and connotation of

misinformation, the data acquisition platform, key research themes, and governance methods.

**Definition of misinformation (RQ 1).** So far, the concept of misinformation has not been uniformly defined. Generally,



**Fig. 6** The distribution of terms related to misinformation.

**Table 4** Definition of different types of misinformation.

	Characteristics	Definition
Disinformation	False, misleading, harmful, and fabricated, and the motives are often politically, economically, and socially relevant.	Information that is intentionally created and falsely disseminated for a purpose.(Swire-Thompson and Lazer, 2020)
Fake news	Harmful, misleading, and the depth of its impact is profound.	Information that contradicts the facts and is fabricated to mimic the content of the news media for some purpose.(Lazer et al., 2018)
Rumor	Time-sensitive, misleading, ambiguous, reversed, and the events tend to be followed by groups of people for a certain period of time.	Information that is widely disseminated without corroboration can be confirmed or falsified.(Zubiaga et al., 2018)
False information	False, misleading, the cause of which may be intentional or unintentional.	Information that is contrary to objective facts.(Ji et al., 2023, Jung et al., 2020)

misinformation broadly encompasses both unintentional misinformation and intentional misinformation (Bodaghi et al., 2023). In existing research, several related terms are also used, such as fake news, rumor, disinformation, false information, misleading information, and so on.

The distribution of keywords related to misinformation across the 3283 articles is illustrated in Fig. 6. It is evident that, from 2013 to 2018, the research primarily concentrated on rumors. However, since 2019, fake news and misinformation have gradually become the focal points of study. Over the past decade, both “rumor” and “disinformation” have remained high-frequency terms in the field of misinformation research. As depicted in Fig. 6, there has been a significant increase in the number of misinformation related articles from 2020 to 2022. The possible reason is that COVID-19 not only posed a serious threat to the world, but also triggered a serious information epidemic in many countries. The information epidemic is closely linked to the COVID-19 epidemic, prompting extensive research within the academic community. After that, interest in misinformation research declined as the pandemic was effectively controlled. In summary, various types of misinformation on social media have become key research focuses in recent years.

In the field of misinformation dissemination, several related concepts exist, including disinformation, fake news, false information, and rumors. These terms share both similarities and differences. Generally, unless specific intentions or contexts are clearly defined, scholars often use these concepts interchangeably. Misinformation can be broadly defined based on the factual accuracy and intent of the information (Guo et al., 2020). However, in real-world situations, it can be challenging for

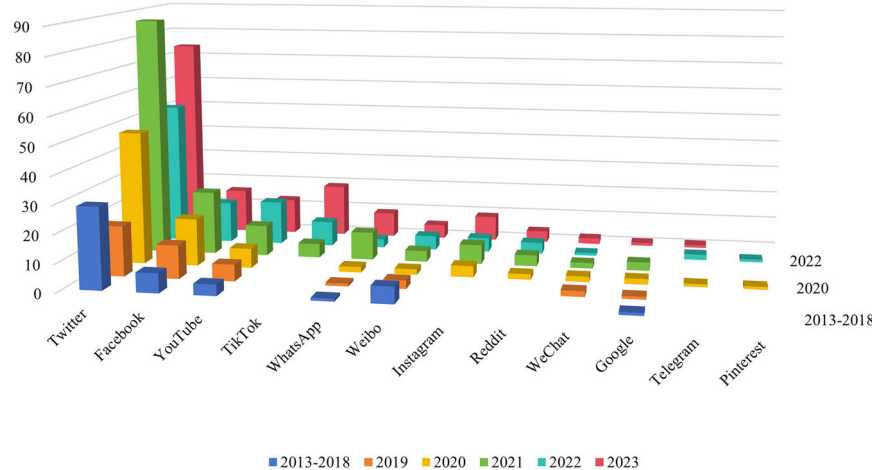
receivers to discern the accuracy and intent of the information (Chen et al., 2023). Misinformation can thus be classified according to its factuality and intent, with the characteristics and definitions of commonly used terms summarized in Table 4.

Table 4 indicates that commonly used terms related to misinformation encompass false, misleading, and harmful information, and it is important to note that these terms are not mutually exclusive. Therefore, clarifying the meanings, scopes and evolutions of the terms will aid in advancing misinformation research. In this study, the scope of misinformation encompasses disinformation, fake news, false information, rumor, and misleading information. To better capture the research dynamics, the term “misinformation” is broadly used to refer broadly to refer to all types of false information content.

**Social media platforms for misinformation research (RQ 2).**

It is widely recognized that online social networks not only enable users to access information but also accelerate the spread of misinformation. To effectively study the mechanisms of misinformation dissemination, detection methods, and governance strategies, researchers must access various social media platforms and gather substantial amounts of data. Figure 7 presents the mainstream social media platforms that have been involved in misinformation research over the past decade.

The rapid development of social media platforms has made information more accessible. However, due to their characteristics of rapid dissemination and anonymity, the spread of misinformation has become a major global research concern. As depicted in Fig. 7, a number of mainstream social media platforms, including Twitter, Facebook, YouTube, WhatsApp, and Weibo, are



**Fig. 7** Social media platforms engaged in misinformation research from 2013 to 2023.

involved in the misinformation related research (Kouzy et al., 2020; Vizoso et al., 2021). For example, Naseem et al. (2021) chose Twitter as an example to investigate the impact of social media during the COVID-19 pandemic, and proactive measures were proven to be effective and efficient in combating negative sentiment on social media. Subsequently, Zhang et al. (2022b) examined the effectiveness of misinformation corrections on Weibo during the COVID-19 pandemic.

Since 2020, a large amount of COVID-19-related misinformation has spread on social media platforms. As one of the most popular short-video social platforms, TikTok has grown rapidly and become a new medium for users to share information since 2021, but it is also riddled with a lot of misinformation. Rovetta and Bhagavathula (2020) examined the search behavior related to COVID-19 and specifically explored the spread of misinformation on Google and Instagram. Bapaye and Bapaye (2021) conducted a special study on WhatsApp to assess the vulnerability of population groups in developing countries to sharing misinformation related to COVID-19. Yeung et al. (2022) investigated the credibility of videos about ADHD on TikTok and found that approximately half of the top 100 most popular videos could be classified as misleading videos. WeChat is characterized by its integration of instantaneous mass communication and interpersonal communication. Zhang et al. (2022a) investigated salient features of health misinformation on WeChat and designed a new strategy to identify health misinformation.

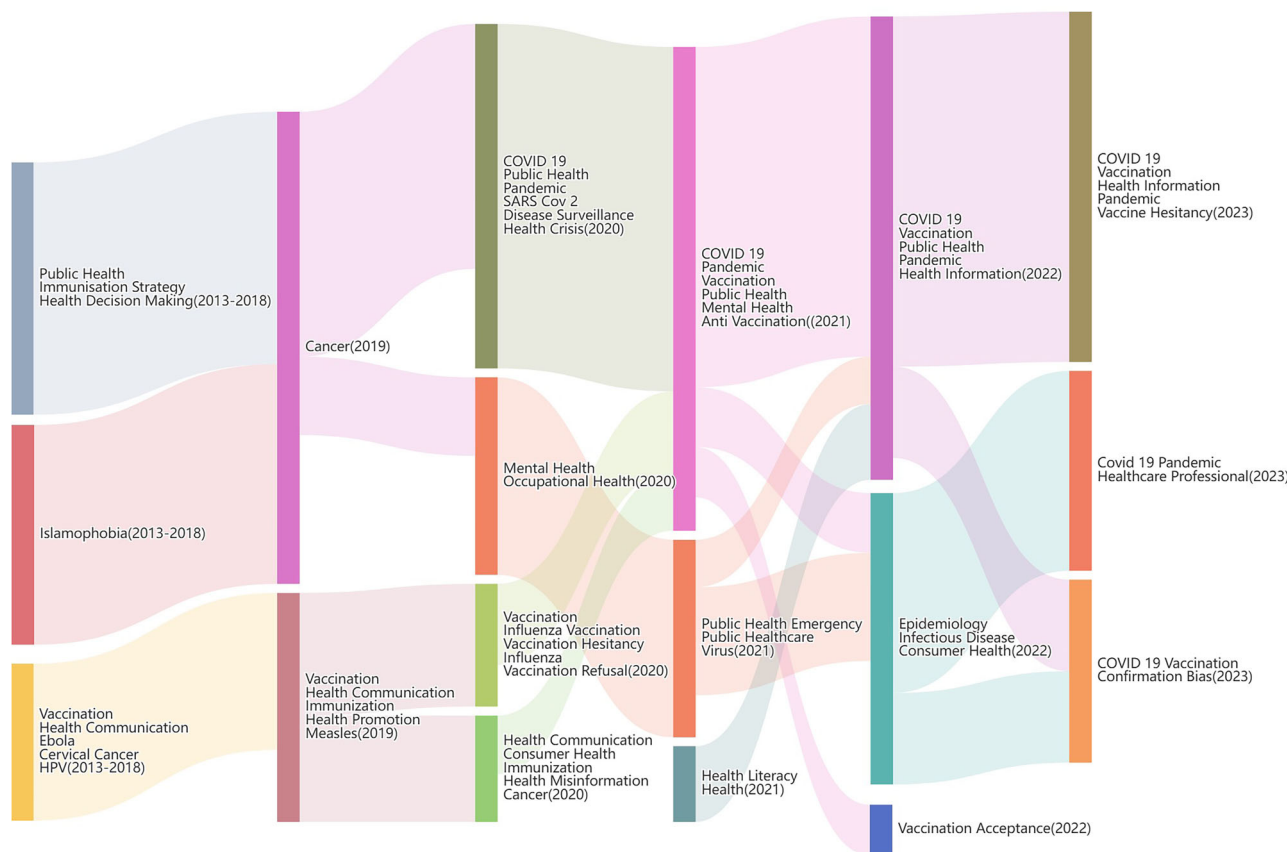
Facebook has the highest number of monthly active users in the world (Statista, 2024), but Twitter is the most cited platform in academic research on misinformation. Twitter's open API architecture allows unrestricted bulk data collection and real-time tracking of information diffusion, making it as a natural laboratory for studying misinformation propagation. In contrast, following the Cambridge Analytica incident (Breuer et al., 2023), Facebook implemented strict data governance policies, including cumbersome compliance processes and restricted API access, which, despite its extensive user base and thus have created significant barriers to large-scale research.

In conclusion, the rapid development of the Internet has transformed information access from traditional media to online platforms. Many researchers have been actively investigating the spread of misinformation on social media sites such as Twitter and Weibo, while interest in WeChat, Instagram, and TikTok continues to grow. With advancements in forgery technology, various media formats, including text, images, audio, and video, are being manipulated to create multimodal misinformation. Additionally, the cross-platform dissemination of misinformation

on social media presents significant challenges to the development of effective detection and governance strategies (Hunt et al., 2020; Murdock et al., 2023; Ruan et al., 2022). Ginossar et al. (2022) argued that future policies and interventions should consider strategies for countering the spread of misinformation through cross-platform activities. More notably, future studies should focus more on these highly active yet less-studied platforms.

**Key research topics of misinformation spread (RQ 3).** The spread of misinformation poses significant risks and harm to people. For instance, health-related misinformation can lead to false beliefs about health practices and may even result in serious medical incidents. During the COVID-19 pandemic, various forms of misinformation regarding treatments led many individuals to misuse non-prescription drugs, greatly increasing the risk of overdose (Shrestha et al., 2022). Similarly, political misinformation can disseminate content that incites social unrest and undermines public trust in relevant authorities (Koetke et al., 2023). The World Health Organization (WHO) has observed that misinformation related to COVID-19 topics can polarize public opinion, increases the risk of conflicts, violence, and human rights violations, thereby threatening the stable development of democracy and social cohesion (The World Health Organization, 2020). Therefore, it is very essential to study the mechanisms of dissemination and mitigation of misinformation in specific context and specific topics. Over the past decade, research on misinformation has exhibited a rich diversity of topics. Key areas of research focus include health information, political information, artificial intelligence, public communication, information credibility, post-truth, influence maximization, conspiracy theory, cybersecurity, and so on. As shown in Fig. 5, health-related misinformation and politics-related misinformation have attracted significant attention from scholars in recent years. In what follows, we will discuss the latest research findings in these two research areas in detail.

*Research themes evolution of health misinformation.* The vast amount of misinformation on social media poses significant challenges for individual health decision-making and cyberspace governance. Many scholars have focused their research on health misinformation. Figure 8 presents a Sankey chart illustrating the evolution of research themes in the field of health misinformation, which shows the dynamic flow and interconnections of research focuses from 2013 to 2023, encompassing topics such as vaccination, COVID-19 response, mental health, and disease



**Fig. 8** The evolution of research themes in health misinformation from 2013 to 2023.

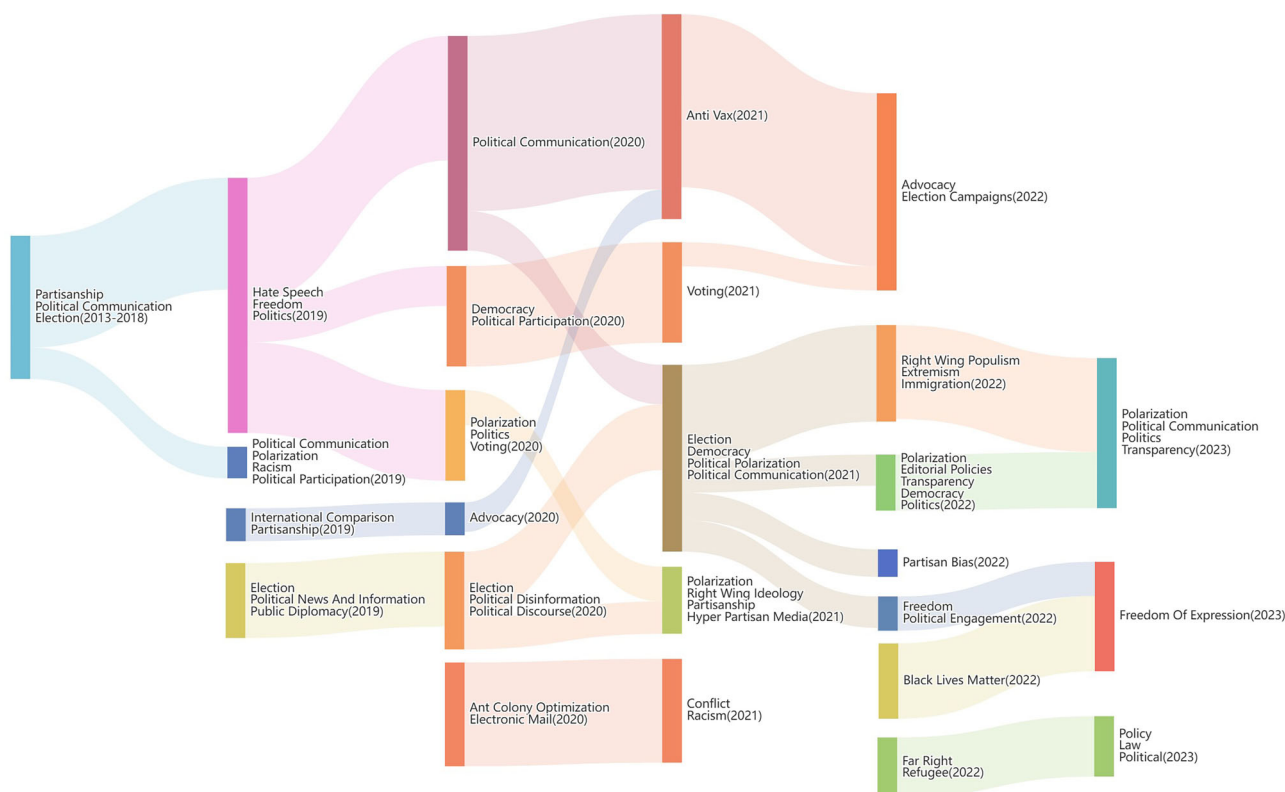
surveillance. It visually illustrates the continuity and transition of public health research priorities over different periods, highlighting the increased focus on COVID-19 related topics in more recent times.

One can see that there is a continued interest among researchers in health information, particularly concerning psychological and physical illnesses, as well as vaccinations. A great number of research has explored various diseases, including Ebola, HPV, cervical cancer, other infectious diseases, and non-specific and specific cancers. Chen et al. (2018) compared the diffusion characteristics of misinformation and true information based on tweets related to two gynecological cancers posted on Weibo. The findings suggested that prevention-related misinformation is more widely disseminated on social media than true information. Massey et al. (2020) collected English-language Instagram posts about HPV between April 2018 and December 2018, and they examined the characteristics of misinformation related to the HPV vaccine on social media. Ball and Maxmen (2020) pointed out that the scientific community should devote more efforts to counter the widespread health misinformation about Vaccination, as one of the most effective measures for the prevention and control of diseases, is also widely discussed on social media (D’Errico et al., 2021). Some researchers explored the typical characteristics of health misinformation and the mechanism of propagation (Bin Naem and Boulos, 2021). The presence of such misinformation and public uncertainty tends to cause anti-vaccination psychology (Nguyen and Catalan-Matamoros, 2022) or vaccination hesitancy (Blane et al., 2022; Teng et al., 2022).

As shown in Fig. 8, before the outbreak of COVID-19, research on health misinformation focused on topics such as traditional diseases and vaccinations. Waszak et al. (2018) examined top

shared news on social media, and they pointed out that most medical misinformation is related to vaccines. The research findings by Jung (2018) indicate that the spread of misinformation about vaccines increases unnecessary anxiety about infectious diseases and may exacerbate hesitation about getting vaccinated. Since the COVID-19 epidemic spread all over the world, misinformation about SARS-CoV-2 and COVID-19 increased significantly on social media in both the scale and speed of dissemination (Kerrigan et al., 2023), thus researchers have turned the emphasis of studying misinformation spread to public health emergency. Kouzy et al. (2020) collected a variety of trending hashtags and keywords related to the COVID-19 epidemic on Twitter to quantify the scale of misinformation spread. Yi and Chiu (2023) collected data sets on Chinese social media in COVID-19 and employed a qualitative method to explore public information needs. In addition, public health emergencies are of immediate concern to the public; misinformation spread on social media may increase dramatically due to the impact of the anxiety, fear, and other psychological factors. Ahmad and Murad (2020) studied the impact of social media on self-reported mental health and pointed out that misinformation spread is likely to cause public anxiety and mental problems on social media. Nowak et al. (2021) used an online cross-sectional study to assess the frequency of COVID-19 prevention behaviors, fears, and beliefs, where they presented some effective suggestions to stabilize public sentiment in infodemic.

In the past decade, there are both continued research themes and many emerging hotspots in the field of health misinformation research. Public health emergencies are also usually accompanied by the widespread dissemination of various health misinformation. Different from other types of misinformation, health misinformation is characterized by many topics, long



**Fig. 9** The evolution of research themes in political misinformation from 2013 to 2023.

duration of dissemination, and various channels of dissemination. It is expected to construct the paradigm of health misinformation research in the future.

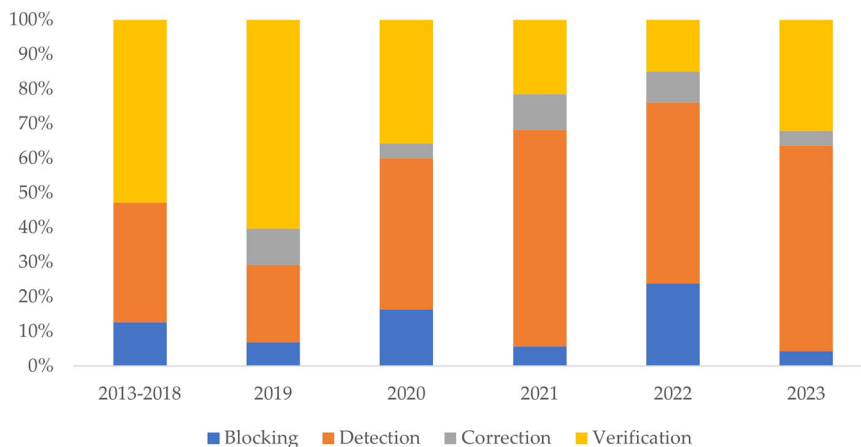
*Research themes evolution of political misinformation.* Political misinformation is closely related to national political security, and it has the potential to influence public opinion, attitudes, and even election results. Figure 9 presents a Sankey chart illustrating the evolution of research topics in the field of political communication. It shows the dynamic flow of research focus from 2013 to 2023, covering issues such as political communication (Tashtoush et al., 2022; Tokita et al., 2021), election (Shin et al., 2017), partisanship (Valenzuela et al., 2021), social movements, including “Black Lives Matter”. This chart intuitively demonstrates the continuation, differentiation, and interconnection of research themes across various periods.

It is worth noting that these research keywords are related to popular political events in recent years. Bennett and Livingston (2018) found that the UK’s Brexit campaign and the election of President Donald Trump are two prominent examples of misinformation spread that undermine the normal democratic order, and explored the roots of these problems and the implications for the political communication research. Landon-Murray et al. (2019) examined the profound impact of political misinformation on public and policy discourse, political accountability and integrity, elections, and governance.

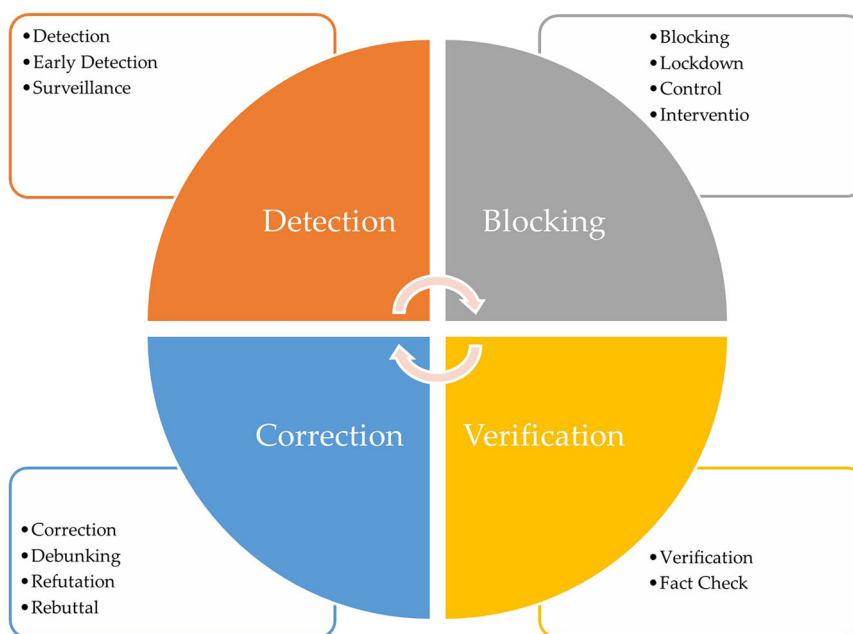
The collected literature indicates that political misinformation is highly correlated with political events. Social media is filled with misinformation about political events, political antagonism, hate speech, racist speech, and other topics. While public political participation and freedom of expression have improved, it has also brought about the spread of hate speech and misinformation on social media. As shown in Fig. 9, research on political misinformation has received much attention in the past decade, and the number of research topics has shown rapid growth.

Especially from 2020 to 2021, the research on political trolling is particularly active because this period is a U.S. presidential election year (Tashtoush et al., 2022; Verma et al., 2021). Meanwhile, the public is highly concerned about political elections, and some researchers explored the dissemination and impact of political misinformation on social media. Wogu et al. (2020) found a growing trend of technological innovation in the dissemination of misinformation on social media, especially during U.S. elections. The main reason is that partisan actors intend to manipulate voters’ preferences. Among the studies of political misinformation, many deal with racism, right-wing forces, nationalism, and so on. For example, Prasad (2022) studied the dissemination of political misinformation and its impact during the campaign against racism (“Black Lives Matter”). To sum up, misinformation not only affects the public’s understanding and judgment of political events but also contributes to social division and instability.

In addition to health and political information, several new research topics have emerged in recent years, including information credibility, blockchain, cybersecurity, echo chambers, and so on (Shahid et al., 2022). As shown in Fig. 5, cybersecurity and blockchain have become significant areas of research since 2019. In this direction, key technologies such as blockchain, artificial intelligence, and machine learning are being explored in the realm of cybersecurity (Blane et al., 2022; Liu et al., 2021). Since 2020, echo chambers and infodemics have increasingly garnered attention in online social media. Accordingly, researchers have incorporated a new context into the study of misinformation dissemination (Bruns et al., 2020; Shahsavari et al., 2020). Meanwhile, with the rise of short videos and the in-depth study of recommendation algorithms, misinformation dissemination on social media platforms become even more challenging. As a result, there is an urgent need for relevant research findings in this area (Bora et al., 2018). In response to the current societal context and public demand, research has diversified and



**Fig. 10** Classification and distribution of misinformation governance research methods (2013-2023).



**Fig. 11** The segmentation of misinformation governance methods.

expanded into various fields, including ecology, the environment, politics, and health. Notably, the phenomena of misinformation dissemination and content related to health and politics are areas that have been consistently explored.

**Misinformation governance methods (RQ 4).** Social media contains huge amounts of information; if the issue of infodemiology in social media is not adequately addressed, it may disrupt the harmony and stability of society (Eysenbach, 2002). The indistinctness and widespread dissemination of misinformation on social media can result in psychological imbalance and behavioral disorders among users, as well as economic and social disruption. Therefore, accurately detecting misinformation and effectively intervening to reduce its spread is critical. Figure 10 shows the classification and distribution of research methods in misinformation governance over the past decade.

Figure 11 displays the segmentation of four misinformation governance methods: detection, blocking, verification, and correction (van der Linden, 2022; Walter and Murphy, 2018). The governance of misinformation on social media encompasses

various aspects, and scholars have conducted research from different perspectives, examining the entire process of misinformation dissemination, detection, and governance. As shown in Fig. 10, the detection of misinformation has been a hot research topic because early detection of misinformation is crucial to effectively reduce the propagation of misinformation on social media (He et al., 2023; Zhao et al., 2021). In this direction, a great number of detection models and approaches have been established, which may be divided into two categories. The first approach detects misinformation by analyzing the syntactic structure, writing style, topic characteristics, and vocabulary of user-generated content. The second approach focuses on exploring the propagation characteristics of misinformation. In 2019, researchers attempted to identify and extract various features, including user, content, dissemination, and emotional aspects, and subsequently developed improved machine learning models to enhance misinformation detection (Liu et al., 2019; Molina et al., 2021). Since 2020, several improved deep learning frameworks have been proposed to achieve more accurate detection of misinformation, utilizing techniques such as convolutional neural networks, graph neural networks, long

short-term memory networks, and recurrent neural networks (Ginossar et al., 2022; Shahsavari et al., 2020).

Blocking misinformation on social media involves reducing the number of nodes activated by misinformation, serving as another effective method of misinformation governance (Ni et al., 2023; Pham et al., 2019; Yang and Li, 2024; Zhu et al., 2020). Influential nodes or interconnected links within social networks play a crucial role in the diffusion of information, and targeting these nodes or edges can significantly hinder the spread of misinformation. Additionally, researchers have developed misinformation blocking models that incorporate clarification mechanisms, wherein influential nodes are selected to disseminate true information, thereby controlling or reducing the spread of misinformation (Biswas et al., 2022; Ni et al., 2023; Pham et al., 2019).

It is important to note that correction and debunking are essential methods for governing misinformation (Sun et al., 2022; Zhou and Zafarani, 2020). Utilizing meta-analysis, Walter and Murphy (2018) explored the differences in corrective actions for three types of misinformation: political, marketing, and health. Vraga et al. (2019) found that the effectiveness of correcting misinformation regarding HPV vaccination significantly increased when utilizing either a logic-based or humor-based approach. By comparing eight fact checkers from the UK, the US, Australia, and Germany, the researchers identified several effective strategies for countering misinformation (Humprecht, 2020; Prasad, 2022; Zhang et al., 2022b). Corrective governance measures tend to be more transparent and costly, often requiring collaboration among multiple parties to effectively trace misinformation and conduct fact-checking (Prasad, 2022; Zhang et al., 2022b). However, a significant advantage of these measures is that social media users become aware of what information is inaccurate and the reasons behind its inaccuracy (Prasad, 2022; Zhang et al., 2022b).

Due to the autonomy, anonymity, and openness of social media, combined with the diverse nature of information dissemination, the time gap between the release and the escalation of misinformation is extremely short. As a result, misinformation can quickly outpace truth information in popularity and reach a wider audience, significantly complicating governance efforts. From the analysis above, it is evident that researchers are actively exploring automated identification technologies for misinformation by analyzing its characteristics and employing techniques such as deep learning. Additionally, relevant authorities are strengthening their engagement on social media by collaborating with opinion leaders to ensure the timely dissemination of accurate information, and effectively addressing the cognitive biases of online users. In the future, it is more crucial to conduct stronger real-time monitoring and detection of posts on social media, as well as to proactively disseminate true information to more active guide users and mitigate the impact of misinformation.

**Limitations and future work.** Most existing research reviews on misinformation have focused on specific topics from the perspective of bibliometrics, such as the connotation and characteristics of misinformation (Caled and Silva, 2022) or governance methods (Bodaghi et al., 2023). This study proposes an integrative framework to systematically analyze the evolution of research topics, hotspots, mainstream methods, and future trends in the field of misinformation dissemination research over the past decade. We construct time-divided keyword co-occurrence networks and identify hot research topics related to misinformation dissemination are identified by using the community detection algorithm, the AHP, and the TOPSIS method.

Notably, key research themes and their evolutionary paths are visualized using a Sankey diagram.

This work has certain limitations that can be addressed in four aspects. First, the sources of research literature will no longer be confined to the Web of Science core database; instead, we will consider additional databases for a more comprehensive analysis. Second, the search strategy is crucial for review articles and will be further optimized to ensure the completeness of the retrieved literature. Third, the information provided by keywords is limited; therefore, we intend to combine the proposed method with NLP tools to explore the research status and development trends based on the title, keywords, and abstract. Finally, the analysis dimension can be further optimized. In future research, we will conduct comparative analyzes on specific research topics from more dimensions, such as considering the geographical information of the authors, to enhance the comprehensiveness of the analysis results.

Existing studies have seldomly focused on the cross-platform diffusion of misinformation on social media, particularly the competition between the dissemination of true information and misinformation across these platforms. While various research methods and models for misinformation detection exist, a hierarchical assessment system for misinformation has yet to be established due to the inadequate accuracy of traditional binary classification methods. With the rapid advancement of artificial intelligence, especially in neural networks and generative adversarial networks, the dissemination and detection of misinformation are becoming increasingly complex. Misinformation is no longer confined to text and images; it is increasingly manifesting in videos. Future research is expected to explore the generation, cross-platform dissemination, emotional evolution, and multimodal recognition of misinformation, as well as deep synthetic detection and traceability.

## Conclusions

With the rapid development of digital technologies, social media platforms have emerged as the primary channels for users to access information and share opinions. However, the convenience of these platforms also facilitates the rapid dissemination of misinformation. Research on misinformation has become a critical and prominent issue, with over 3283 research papers published in the Web of Science Core Collection over the past decade.

In this study, we first summarize commonly used terms in the field of misinformation dissemination by comparing the meanings, scopes, and evolutions of various concepts. Next, we compare the most frequently analyzed social media platforms in misinformation research. Additionally, we propose a novel method for analyzing the evolution of several research hotspots, including health misinformation, political misinformation, and methods of misinformation governance.

As for the initial four questions, the answers can be summarized as follows. **For RQ1**, the literature survey reveals a notable increasing trend in the amount of scholarly works concerning the definition of misinformation, which not only demonstrates the academic attention to the topic but also emphasizes a thorough exploration of the concept and scope of misinformation. **For RQ2**, the increasingly diverse social media platforms make it more convenient for people to access information. Traditional mainstream media such as Twitter and Facebook, as well as emerging media platforms such as WeChat and TikTok, provide more empirical datasets for related studies. **For RQ3**, the literature gathered in this study comprises a total of 7714 keywords. High-frequency keywords include terms such as health, vaccination, politics, detection, and cybersecurity. While key research themes exhibit a trend towards diversification, health and political misinformation have been of continuous interest to scholars over

the past decade. Through interdisciplinary integration and ongoing innovation in research methods, numerous significant findings in the field of misinformation research have been achieved. For RQ4, a series of studies focus on governance strategies for misinformation, including measures such as early warning systems and account isolation. In emergency situations, managing misinformation on social media may require the integration of various methods, including detection, blocking, verification, and correction of false information.

This work offers a comprehensive overview of research on the dissemination of misinformation on social media over the past decade, emphasizing both theoretical and practical implications. On one hand, the research framework established in this paper, integrating complex networks, community segmentation, TOPSIS, and the AHP method, reveals the thematic evolution and development trends of misinformation dissemination on social media. This framework can also be applied to assess research advancements and future directions in other fields. On the other hand, the findings of this study may provide valuable insights for upcoming misinformation research and serve as a reference for formulating effective governance strategies.

### Data availability

The research materials utilized in this study consist of publicly accessible articles from online journals or library databases.

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### Author contributions

Conceptualization, methodology, funding acquisition, supervision, and writing—review and editing, G.X.; methodology, software, resources, data curation, visualization, and writing—original draft preparation, M.Q.; investigation, resources, validation, formal analysis, and writing—review and editing, L.M. All authors have read and agreed to the published version of the manuscript.

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The authors declare no competing interests.

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

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