A Survey on the Role of Crowds in Combating Online Misinformation: Annotators, Evaluators, and Creators

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Online misinformation poses a global risk with significant real-world consequences. To combat misinformation, current research relies on professionals like journalists and fact-checkers for annotating and debunking false information, while also developing automated machine learning methods for detecting misinformation. Complementary to these approaches, recent research has increasingly concentrated on utilizing the power of ordinary social media users, a.k.a. "the crowd", who act as eyes-on-the-ground proactively questioning and countering misinformation. Notably, recent studies show that 96% of counter-misinformation responses originate from them. Acknowledging their prominent role, we present the first systematic and comprehensive survey of research papers that actively leverage the crowds to combat misinformation.

In this survey, we first identify 88 papers¹ related to crowd-based efforts, following a meticulous annotation process adhering to the PRISMA framework (preferred reporting items for systematic reviews and meta-analyses). We then present key statistics related to misinformation, counter-misinformation, and crowd input in different formats and topics. Upon holistic analysis of the papers, we introduce a novel taxonomy of the roles played by the crowds in combating misinformation: (i) *crowds as annotators* who actively identify misinformation; (ii) *crowds as evaluators* who assess counter-misinformation effectiveness; (iii) *crowds as creators* who create counter-misinformation. This taxonomy explores the crowd's capabilities in misinformation detection, identifies the prerequisites for effective counter-misinformation, and analyzes crowd-generated counter-misinformation. In each assigned role, we conduct a detailed analysis to categorize the specific utilization of the crowd. Particularly, we delve into (i) distinguishing individual, collaborative, and machine-assisted labeling for annotators; (ii) analyzing the effectiveness of counter-misinformation through surveys, interviews, and in-lab experiments for evaluators; and (iii) characterizing creation patterns and creator profiles for creators. Finally, we conclude this survey by outlining potential avenues for future research in this field.

CCS Concepts: • Information systems → Data mining; Social networks.

Additional Key Words and Phrases: misinformation, combat misinformation, crowd, survey, counter-misinformation

 $^{1} https://github.com/claws-lab/awe some-crowd-combat-misinformation \\$

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1 INTRODUCTION

Most individuals today rely on social media platforms as their primary source of news and information [99]. However, such platforms contain a plethora of unreliable information, including misinformation, which unfortunately spreads more rapidly and widely than truth [97]. Online misinformation harms individuals and society at multiple levels. At the micro-level, misinformation harms well-being [94], increases polarization [82], and leads to online harassment and violent attacks on individuals and communities [20]. At the macro-level, misinformation questions democratic processes and elections [79], impacts science and global public health [22, 55, 107]. For instance, misinformation about the COVID-19 vaccine (e.g., the vaccine causes infertility) has reduced vaccine uptake and prolonged the pandemic [22, 55, 107]; misinformation about elections can undermined trust in democratic processes and institutions [21]. Therefore, it is crucial to curb the spread of online misinformation and to counter misinformation [85, 97, 112].

Motivated by this, research has focused on detecting misinformation by utilizing different approaches, including automated machine learning (ML) solutions [30, 38, 76] and the use of professional fact-checkers [50, 56, 70]. Notably, there has been a growing interest in research on developing ML models [76] based on post content, poster attributes, social network, temporal aspects, and propagation features [77]. These models have been deployed across widely-used web and social media platforms (e.g., Twitter, Facebook, and Youtube). In the meantime, ML solutions rely on ground truth labels of misinformation for their training and validation, whereas professional fact-checkers typically label the misinformation with fact-check labels. These professionals also write fact-checking articles to explain their reasoning for the label determinations. For example, *Snopes.com* provides fact-check labels that range from "true" and "mostly true" to "mostly false" and "false", accompanied by corresponding explanations.

Despite these solutions, the "infodemic", or the epidemic of misinformation [11, 16, 107], continues to grow at an alarming rate. One contributing factor is that automated ML models respond slowly to changes in the information ecosystem, rely on fact-check labels provided by professional fact-checkers, and are vulnerable to manipulation by adversaries [4, 32, 74]. On the other hand, professional fact-checkers face limitations in terms of the limited number of fact-checkers and the significant time required for label generation; moreover, their fact-checks tend to address only a small number of viral claims [4, 56, 68]. Importantly, both approaches only detect misinformation but do not actively engage with misinformation spreaders. In this context, it is worth noting that there has been a noticeable absence of discussion on structured methods for countering misinformation once it is identified.

1.1 Motivation

To address the drawbacks of these two approaches, leveraging **crowds** offers a promising solution for combating misinformation in a scalable and proactive manner [4, 48]. In this study, we focus on the "crowd" — defined as *ordinary users of social media platforms* (i.e., not fact-checkers, journalists, or organizations). They serve as eyes on the ground who proactively question and counter misinformation, including emerging misinformation [10, 33]. Literature has shown that crowd-based "social correction" is effective and works well across topics [10, 48]. Crowds engage in combating misinformation by contributing significant benefits in diverse tasks, including identifying misinformation, assessing counter-misinformation effectiveness, and creating counter-misinformation. In addition, crowds also have the key benefit of being "**cost-effective**," compared to the expensive and time-consuming recruitment of professional Manuscript submitted to ACM

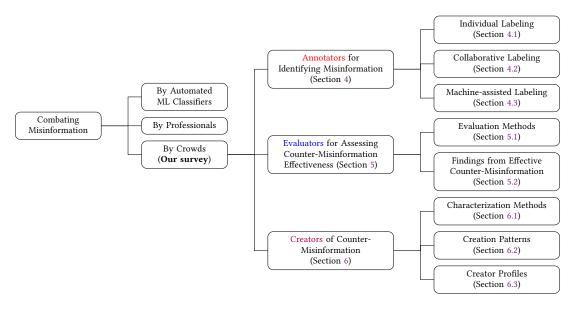


Fig. 1. Two existing approaches to combat misinformation and our proposed taxonomy hierarchy related to crowd-based efforts.

fact-checkers. Crowds on social media platforms often counter online misinformation voluntarily [5, 61], making it cost-effective to leverage their collective efforts. Therefore, there has been a surge of research efforts to develop <u>crowd-based</u> methodologies to annotate misinformation, evaluate counter-misinformation effectiveness, and characterize <u>counter-misinformation creation</u> in recent years [4, 9, 17, 61, 75, 102, 103, 111]. Given the growing and significant interest in this area, we investigate the crowd-based research efforts in combating online misinformation.

1.2 Our Work

In this survey, we aim to provide a comprehensive overview of the collaborative efforts made by crowds in combating misinformation. To clarify our scope, we focus on online misinformation², rather than all information or offline information. More specifically, our investigation centers on recent and actively pursued initiatives in *combat misinformation* within this field.

We first identify 88 relevant papers by following the guidelines of the preferred reporting items for systematic reviews and meta-analyses (PRISMA framework) [59] (Section 2). We then present a detailed overview of misinformation formats, topics, social media platforms, and crowd inputs (Section 3). Upon holistic analysis of the papers, we propose a novel taxonomy of the crowd-based efforts that aim to combat misinformation, as depicted in Figure 1. To this end, we categorize crowd users based on their *roles*, as shown in Figure 2:

• Crowds as Annotators: Crowds help *identify and label* online misinformation accurately at scale [9], leveraging their extensive numbers compared to the limited professional fact-checker pool, and their widespread presence across social media platforms. Additionally, crowds can *amplify* the efforts of fact-checkers by sharing fact-checking articles to combat misinformation out of a sense of social responsibility [65], driven by emotions such as anger or concern provoked by fact-checks [86], and a desire to warn others against misinformation [93].

²The term "misinformation" in this survey is commonly represented as the terms "fake news", "rumor", "false information", "false news", and "conspiracy theory."

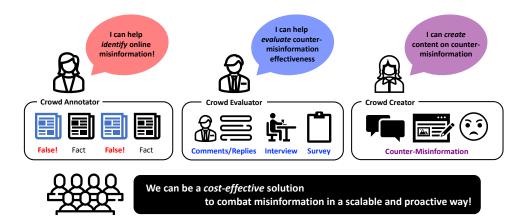


Fig. 2. Illustration of the roles of crowds in combating misinformation.

- Crowds as Evaluators: Crowds help evaluate the effectiveness and limitations of different counter-misinformation
 messages across various aspects. They contribute by providing their first-hand experiences and tangible responses
 to misinformation and counter-misinformation. This valuable input facilitates the design of effective strategies to
 counter misinformation and offers a unique perspective not always accessible to professional fact-checkers [11].
- Crowds as Creators: Crowds create their own content on social media platforms to combat misinformation
 through these crowd-generated posts [20, 62]. They also respond to and comment on misinformation with
 accurate information [30]. Analyzing such activities allows us to characterize the creators and patterns of their
 counter-misinformation messages.

We frame our examination of this topic around three research questions (RQs) that naturally align with the aforementioned roles of the crowds:

- (RQ1) Capabilities of crowds in identifying misinformation: How do crowds contribute to identifying or detecting misinformation, and how effective are they in this task?
- **(RQ2) Evaluation of counter-misinformation effectiveness by crowds**: How can crowds be leveraged to evaluate counter-misinformation efficacy, and how effective are different types of counter-misinformation?
- (RQ3) Characterization of counter-misinformation messages by crowds: What are the characteristics of crowd-generated counter-misinformation messages and crowds who counter misinformation?

However, addressing the above RQs systematically poses several challenges. First, online misinformation spans a wide range of topics, including politics and natural disasters, and is disseminated across various platforms like Twitter and YouTube. Meanwhile, crowds engage differently based on their roles, which include identifying misinformation, evaluating counter-misinformation effectiveness, creating counter-misinformation content, and responding to misinformation messages. Additionally, they counter misinformation across a range of content formats, including text and images. Lastly, researchers employ diverse approaches, such as in-lab experiments, interviews, and surveys, when analyzing crowd-based efforts in countering misinformation.

To navigate these challenges, our work to address each RQ can be summarized as follows:

Crowds as annotators for identifying misinformation (for RQ1; Section 4): We investigate the capability
of crowds to identify misinformation and compare it with that of professional fact-checkers. We analyze both
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Table 1. Comparison with existing surveys. In this table, \checkmark and \checkmark denote that the relevant survey fully and partially covered the corresponding topic, respectively.

	Crowds' Roles		
	Annotators for identifying misinformation	Evaluators for assessing counter-misinformation	Creators of counter-misinformation
[84, 104] [30, 76, 78]	· ·		
[13, 31] Our work	✓	[13]: √ , [31]: ⋰ ✓	✓

individual and collective labeling scenarios, as well as the machine-assisted setting where humans and machines collaborate to enhance the annotation performance.

- Crowds as evaluators for assessing the effectiveness of counter-misinformation (for RQ2; Section 5): We examine direct and indirect evaluation methods, including expressed sentiment and stance, in-lab experiments, interviews, and surveys, to quantitatively evaluate the efficacy of a given counter-misinformation message. Then, we investigate the distinct advantages offered by each counter-misinformation approach.
- Crowds as counter-misinformation creators (for RQ3; Section 6): We examine two aspects of counter-misinformation characteristics: i) the characteristics of counter-misinformation messages generated by the crowds on social media platforms; ii) typical attributes of crowds who counter misinformation.

Through these investigations, we provide valuable insights into the effectiveness and limitations of existing crowdbased efforts in combating misinformation.

1.3 Related Survey

While most surveys on misinformation primarily focus on automated machine learning solutions [38], it's worth noting that a few surveys [13, 30, 31, 76, 78] explore the literature that covers crowd-based efforts. However, these previous surveys have certain limitations, and we aim to provide a more comprehensive perspective. Here's a comparison between our survey and previous ones, as shown in Table 1.

First, some surveys [30, 76, 78] have examined crowds' ability to *identify misinformation* (i.e., annotators). They only deal with inferring misinformation-related signals from indirect crowd behaviors, such as replies and comments, and incorporating those signals into ML solutions as labels. However, as mentioned in Section 1.1, our survey recognizes and investigates the potential for crowds to serve as a direct and potent means for accurately identifying and labeling misinformation at a large scale. This distinction sets our survey significantly apart from the aforementioned prior research. Second, Chan et al. [13] summarize the effectiveness of various types of counter-misinformation *evaluated by crowds* (i.e., evaluators). However, this survey has limitations as it only covers 8 papers, is restricted to literature published before 2018, and does not provide a comprehensive summary of the evaluation methods employed by crowds. Hartwig et al. [31] analyze the user-centered misinformation interventions where crowds implicitly or explicitly evaluate certain intervention techniques. Nevertheless, some evaluated interventions are not related to counter-misinformation contents, e.g., the removal of misinformation. In contrast, our survey addresses these limitations through a rigorous paper search process for recent papers and summarizes the assessment metrics and methods used to evaluate the efficacy of counter-misinformation. Third, none of the existing surveys cover the *characterization of counter-misinformation*

from the perspective of the crowds (i.e., creators). This is a notable gap as understanding the characteristics of crowd-generated counter-misinformation can offer valuable insights for devising effective strategies to combat misinformation. Our survey fills this gap by providing a comprehensive analysis of the patterns of existing counter-misinformation messages generated by crowds, as well as identifying and profiling typical attributes of these crowd creators.

1.4 Contributions

In sum, the main contributions of this survey are:

- Comprehensive Survey: We systematically identify the relevant papers on the crowd-based efforts in combating misinformation and then review them in terms of detection of misinformation, evaluation of countermisinformation effectiveness, and characterization of counter-misinformation creation. To the best of our knowledge, this is the first review of the literature that encompasses crowds' contributions to these three crucial aspects.
- **Key Statistics:** We summarize important data statistics regarding misinformation and crowds found in the literature (88 papers³). This encompasses the common formats and topics of misinformation, the social media platforms where crowds engage, and the inputs made by the crowds.
- **Novel Taxonomy:** We provide a novel taxonomy of approaches that comprehensively covers the diverse functions of crowds. This is designed to help researchers understand the current research trends in this area.
- Thorough Analysis: We conduct a comprehensive analysis of each crowd role, including individual, collaborative, and machine-assisted labeling for annotators, as well as survey, interview, and in-lab experiment-based countermisinformation effectiveness assessment for evaluators, and the characterization of creation patterns and creator profiles for creators.
- Future Directions: We discuss the limitations of existing crowd-based approaches to combat misinformation
 and suggest several promising research directions for the future.

2 METHOD OF IDENTIFYING RELEVANT PAPERS

Following PRISMA guidelines [59], we conducted a comprehensive search for relevant papers on *www.scopus.com*, a reputable scientific database. The following query was executed on September 22, 2022, and yielded 3,956 papers.

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TITLE-ABS-KEY ( (Category #1) AND ( Category #2 ) AND ( Category #3 ) AND ( Category #4 ) ) AND PUBYEAR > 1999 AND ( LIMIT-TO ( LANGUAGE, "English" ) )
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We specifically targeted research articles in English published after 1999. The search utilized information from titles, abstracts, and keywords of these articles, referred to as "TITLE-ABS-KEY". The search combined four categories of information using logical "AND". These categories and their definitions are provided in Table 2. Keywords within each category were combined using the "OR" operator to ensure that all related concepts were included, and the wildcard "*" was used to account for multiple spelling variations. Specifically, Category 1 deals with terms related to crowds, particularly non-experts, engaged in countering misinformation. Category 2 is related to online platforms where crowd reactions to misinformation are observed. Category 3 covers misinformation-related terms and synonyms. Lastly, Category 4 indicates actions that hinder the spread of misinformation.

³https://github.com/claws-lab/awesome-crowd-combat-misinformation

Table 2. The collection of keywords used to search relevant papers.

To ensure the inclusion of only relevant papers in our survey, we rigorously followed PRISMA guidelines and established the following inclusion criteria: First, the paper must explicitly mention *crowds' active community engagement*. This involvement typically encompasses crowd inputs such as annotations, replies to, or comments on online misinformation; or responses related to counter-misinformation collected through surveys, in-lab experiments, and interviews. Second, the purpose of the aforementioned efforts or the associated research papers should be *combating misinformation*. This implies that the paper should employ these efforts to mitigate the negative impacts of misinformation and promote the positive effects of counter-misinformation, so as to counter misinformation. These actions may include detecting misinformation, evaluating counter-misinformation effectiveness, and characterizing counter-misinformation.

These criteria were established through extensive discussions between two authors to ensure the selection of papers within the intended topic. Each author initially assessed a batch of 200 papers together. Papers were categorized as "Yes" if they explicitly met both criteria, "No" if they didn't focus on the research topic or were proposal articles, and "Maybe" if there was some degree of confidence in their relevance. Subsequently, an inter-rater reliability analysis was conducted, yielding a Krippendorff's alpha score [45] of 0.571, indicating a moderate level of agreement [54]. This seemingly low but acceptable value accounts for some overlap between "Maybe" and "Yes" labels, which was resolved during the collaborative review. Moreover, only papers covering the aforementioned aspects related to the detection, evaluation, or characterization were retained. Ultimately, this comprehensive process identified 88 papers for our survey. Figure 3 displays the annual distribution of our selected papers categorized by the role of the crowd.

3 DATA STATISTICS OF PAPERS

We provide a summary of the selected papers in the survey, examining relevant statistics regarding the formats of misinformation, covered topics, utilized social media platforms, and crowd inputs. This overview offers scholars a preliminary understanding of the research field.

3.1 Misinformation

3.1.1 Formats and Topics. Countered misinformation mainly comprises textual content, encompassing textual posts on social media platforms. Research has explored a diverse range of misinformation topics, as summarized in Table 3-(a). These topics consist of politics (e.g., elections [21] and immigration [52]); natural disasters (e.g., earthquakes [62] and climate change [9]); health issues (e.g., COVID-19 pandemic [12, 42, 57, 107], vaccines [29, 83, 107], and genetically Manuscript submitted to ACM

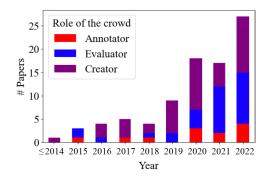


Fig. 3. Annual distribution of annotated relevant papers in our survey categorized by the role of the crowd.

Table 3	Overview	of misinforma	tion statistics	in surveyed	naners

	Catego	ries	References
	Politics		[19-21, 23, 28, 47, 51, 52, 75, 80]
cs	Natural Disasters		[9, 26, 36, 47, 62, 100, 105]
opi	Health Issues		[2-4, 10, 11, 25, 29, 37, 41, 42, 52, 55, 57, 65, 66, 83, 86, 92, 93, 98, 107]
(a) Topics	Crisis Events		[6, 8, 39, 46, 53, 100, 110, 112, 113]
<u>a</u>	Civic Topics		[4, 7, 8, 19, 20, 47, 49, 64, 66, 68, 87, 90, 91]
	General Topics		[27, 43, 58, 65, 73, 96]
-	Social Media	Twitter	[2, 6-8, 12, 14, 19, 26-29, 36, 39, 46, 55, 57, 62, 64, 66, 100, 105, 113]
		Facebook	[3, 4, 14, 26, 107]
		YouTube	[12, 42]
ns		Reddit	[1, 23]
, O.L.		Sina Weibo	[47, 110]
latt		Zhihu	[15]
(b) Platforms		Whatsapp	[44]
	Crowdsourcing	AMT	[25, 51, 68, 80, 86]
		Others	[9-11, 21, 37, 41, 43, 49, 52, 53, 58, 63, 65, 72, 75, 83, 85, 87, 91-93, 98, 112]
	Other Platforms		[65, 73]

modified organisms [15]); crisis events (e.g., mass shooting [46]); and other civic subjects, including rumors about brands KFC [64, 66], celebrities [19, 20], and movies [7, 8]. The research also addresses generic misinformation topics obtained from online fact-checking sources like *Snopes.com* and *PolitiFact.com* [43, 96].

3.1.2 Platforms. The crowds actively combat misinformation across various online platforms where they primarily work as counter-misinformation creators, including social media platforms like Twitter and Facebook. Additionally, crowd-sourcing platforms like Amazon Mechanical Turk (AMT) are leveraged to collect annotation of misinformation and evaluation of counter-misinformation from crowds. A summary of these platforms can be found in Table 3-(b). Manuscript submitted to ACM

Categories		ategories	References	
(a) Format		Text Image Video	[2, 6, 15, 26–28, 39, 44, 47, 55, 57, 64, 100, 107, 110] [12, 19, 23, 64] [42]	
tures	Explicit	Flagging Misinformation Credibility of News Debunking Websites Countermeasures Demographics Media Literacy Emotion Conspiracy Mentality	[5, 61] [4, 9, 10, 41, 43, 49, 51, 53, 58, 63, 91, 92, 98] [4, 53, 57, 68, 93] [10, 21, 25, 41, 43, 51, 52, 65, 66, 73, 75, 83, 86, 91, 92] [37, 65, 66, 112] [72, 93, 98] [72, 85, 92] [10, 49, 63]	
(b) Features	Implicit	Textual Embedding Psycholinguistic Features Topic Sentiment Emotion Hashtag URL Number of Likes/Shares Group Identity Language	[57] [19, 27, 29, 55, 57, 66, 75, 107] [23, 75] [23, 47, 57, 66, 75] [42] [2, 7, 105] [2, 19, 36, 39, 57, 105] [36, 64] [15]	

Table 4. Overview of crowd inputs statistics in surveyed papers.

3.2 Crowd Inputs

3.2.1 Content Formats. Crowds counter misinformation through diverse content formats, as outlined in Table 4-(a). The primary involves utilizing various textual formats such as posting counter-misinformation content, commenting on news articles, replying to social media posts, and retweeting or sharing corrective information [2, 6, 26, 28, 39, 47, 55, 64, 100, 110]. Additionally, images often supplement textual content to enhance the effectiveness of countering misinformation [19, 64]. Lastly, video content serves as an effective tool to debunk misinformation on platforms like YouTube and has demonstrated its potential to educate the general public [42].

3.2.2 Features Extracted from Crowd Inputs. Crowds provide a diverse range of content in response to misinformation, offering researchers valuable features that can be utilized for misinformation detection and counter-misinformation characterization. In this survey, we categorize them into explicit and implicit features, as shown in Table 4-(b). Explicit features involve a direct examination of raw inputs. This includes activities such as rating and flagging misinformation [5, 61], assessing credibility scores of news articles [4, 9, 10, 41, 43, 49, 51, 53, 58, 63, 91, 92, 98], identifying valuable debunking websites [4, 53, 57, 68, 93], suggesting countermeasures [10, 21, 25, 41, 43, 51, 52, 65, 66, 73, 75, 83, 86, 91, 92], and collecting demographic attributes of users [65, 66]. Implicit features, on the other hand, are derived through computational methods applied to raw inputs. These methods generate new feature vectors, such as textual embeddings [57], psycholinguistic features [19, 27, 29, 55, 57, 66, 75, 107], and sentiment [23, 47, 66, 75] and other computational metrics [2, 7, 15, 19, 36, 39, 47, 57, 64, 105] for (counter-)misinformation analysis.

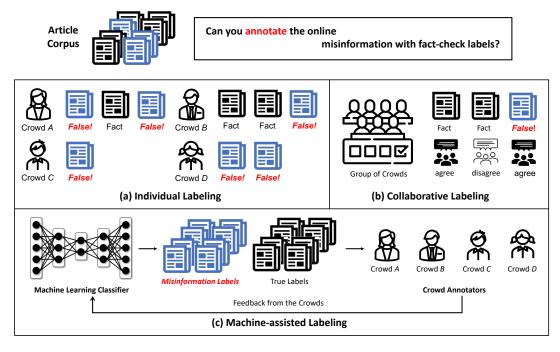


Fig. 4. Illustration of crowds' role as annotators for identifying misinformation.

4 CROWDS AS ANNOTATORS FOR IDENTIFYING MISINFORMATION

Following our meta-level summary of relevant papers, we now dive deeper into the functional categorization of the roles of crowds. Our taxonomy, represented in Figure 2, categorizes the contributions of crowds along three axes: annotators, evaluators, and creators. In this section, we focus on the "annotator" category, where crowds serve as annotators for identifying misinformation.

To identify misinformation, many ML methods have emerged for automated detection [76]. However, these methods heavily rely on the expertise of fact-checkers to obtain ground-truth annotations (e.g., fact-check labels), whose population and bandwidth are unfortunately limited. In contrast, emerging approaches involve harnessing the fact-checking competence of the crowd, especially laypeople, for efficient and effective misinformation annotation [58, 73]. In this context, crowds can directly label potential misinformation articles. Notably, recent research suggests that crowd-based annotation performance rivals that of professionals [9, 74], enabling the use of these labels in downstream tasks such as misinformation classification [75] and (counter-)misinformation analysis [28]. Therefore, we review the relevant studies where crowds annotate misinformation. These studies fall into three key categories: individual labeling of misinformation, collaborative labeling by a group of annotators, and machine-assisted labeling with crowd inputs. Figure 4 provides a visual representation, and Table 5 offers a comprehensive list of reference papers. We then provide detailed descriptions of each category in the subsequent subsections.

CategoriesReferencesIndividual Labeling[9, 58, 73, 74, 106]Collaborative Labeling[5, 61]Machine-assisted Labeling[24, 58, 73, 75]

Table 5. Taxonomy of crowd annotators for identifying misinformation.

4.1 Individual Labeling

Individual labeling of misinformation requires independent judgments about the credibility of the given misinformation by each crowd member. To accomplish this labeling, platforms such as Amazon Mechanical Turk [74] and Upwork [9] facilitate direct user labeling [58, 73]. On these platforms, labels obtained from crowds are typically verified through majority voting. During this process, the credibility levels of the crowds increase as they accurately identify misinformation.

Furthermore, several factors have been explored that influence the quality of individual labeling [9, 74, 106]. One significant factor is evidence from other peers [106], which can either aid or mislead crowds in their judgments. Crowds who effectively use provided evidence tend to make more accurate annotations. Moreover, the demographic and political composition can also influence crowds' credibility ratings and annotations. For example, Bhuiyan et al. [9] found that Democrats, males, those between the ages of 26 and 30, and those with higher levels of education are more likely to agree with experts on climate science.

Additionally, characteristics of the annotation task itself, such as the genre of the article and partisanship of the publication, also have an impact. Bhuiyan et al. [9] found that crowds demonstrate a higher correlation with experts in opinion articles and left-leaning publications. Lastly, the length of the annotation period can also affect the quality of the judgments made by crowds. Notably, Roitero et al. [74] found that annotations collected at different time spans for the same document may yield different results. Annotations collected in close proximity to each other tend to produce similar outcomes.

4.2 Collaborative Labeling

In addition to individual labeling, collaborative labeling indicates that multiple individuals are contributing to annotations collaboratively, which enhances quality through shared insights and community engagement [5, 61]. Twitter's Birdwatch/Community Notes⁴, introduced in 2021, is a prominent example. In this initiative, crowds review the annotations of others and then label tweets that may contain misinformation by providing supporting material and annotations of others. It is worth noting that, unlike majority-based aggregation commonly used in individual labeling scenarios, collaborative labeling involves group-level interactions that occur *before* final label consensus. This aspect makes collaborative labeling a more crowd-enabled process compared to individual labeling. Subsequently, research efforts have emerged to investigate and address challenges within the Birdwatch collaborative labeling ecosystem. For instance, crowds have different levels of credibility in their annotations, which can result in biased or unfair labeling. To tackle this issue, Mujumdar and Kumar [61] proposed HawkEye, a robust reputation system for fair user ranking and misinformation labeling. Additionally, Allen et al. [5] investigated the impact of crowds' partisanship within the Birdwatch annotation process. They found that crowds tend to offer negative annotations for tweets from counter-partisans and consider their annotation less helpful.

⁴https://help.twitter.com/en/using-twitter/community-notes

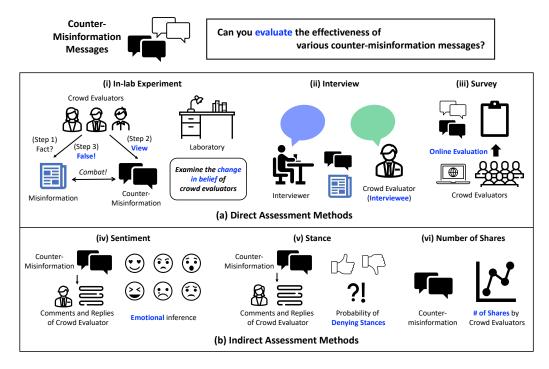


Fig. 5. Illustration of crowds' role as evaluators to assess counter-misinformation effectiveness.

4.3 Machine-assisted Labeling

Machine-assisted labeling methods combine computational power and crowd inputs to efficiently detect misinformation [58, 75]. In the human-in-the-loop pipeline proposed by Shabani and Sokhn [75], crowds initially verify misinformation labels assigned by ML classifiers, and this feedback is then used to refine the classifiers [75]. Additionally, Farooq et al. [24] proposed a blockchain-based framework that leverages the inherent immutability and incentive features of blockchains to record crowd annotations, ensuring accountability while also rewarding accurate contributions and penalizing malicious annotations. Similarly, Ramachandran et al. [73] incorporated the blockchain framework to collect the given genuineness score of news articles from crowds to improve the downstream fake news detection algorithms. Lastly, topic modeling techniques can be used to cluster tweets on similar topics, and crowds can assess the credibility of these tweets to ensure a coherent and consistent annotation process [58].

5 CROWDS AS EVALUATORS FOR ASSESSING COUNTER-MISINFORMATION EFFECTIVENESS

Once misinformation is identified by crowds, ML classifiers, or professionals, different counter-misinformation messages are created on social media platforms. In this case, crowds can help evaluate the effectiveness and limitations of various counter-misinformation messages. To introduce evaluation methods utilizing crowds as evaluators in the literature, we categorize them into two categories, i.e., direct and indirect assessments by crowds (see Figure 5). Each category consists of three sub-categories: direct assessment-in-lab experiment, interview, and survey; indirect assessment-sentiment, stance, and number of shares. Next, we describe the details of each category and then discuss findings regarding effective counter-misinformation across different factors, such as media formats, countering order, word placement, content Manuscript submitted to ACM

Categories		Categories	References	
ethods	Direct	In-lab Experiment Interview Survey	[4, 10, 22, 25, 40, 41, 41, 43, 51–53, 67–69, 80, 83, 86, 87, 89, 92, 98, 109 [11] [40, 43]	
(a) Meth	Indirect	Sentiment Stance Number of Shares	[111] [102, 103] [17]	
(b) Findings	Media Formats Content Traits Communication Styles Audience Factors Countering Order Word Placement		[40, 43, 52, 67, 93, 98, 108, 109] [40, 43, 63, 83, 102, 109] [41, 52, 63, 103, 109] [67, 71, 88, 103, 108] [22, 89] [69]	

Table 6. Taxonomy of crowd evaluators for counter-misinformation effectiveness.

traits, communication styles, and audience-related factors, in the subsequent subsections. The taxonomy of evaluation methods and factors can be found in Table 6-(a) and -(b), respectively.

5.1 Crowd-based Evaluation Methods

As mentioned above, two evaluation methods can be employed to evaluate the efficacy of counter-misinformation using crowd input. The first method, referred to as *direct assessment*, involves the use of direct quantitative questions in which crowds rate the believability of misinformation after encountering counter-misinformation messages. This approach directly assesses the preferences and perceptions of the crowd, with lower believability indicating more effective countermeasures. In contrast, the second method, termed *indirect assessment*, involves the use of indirect indicators or proxy metrics. To this end, we can analyze attitudes expressed in the comments and fact-checking shares of the crowds to indirectly measure the effectiveness of countering misinformation.

5.1.1 Direct Assessment. Direct assessment of counter-misinformation through quantitative questions involves various research methodologies, including in-lab experiments, interviews, and surveys. In-lab experiments are a common approach in many studies [22, 40, 41, 52, 67, 69, 83, 89, 98]. Crowds are presented with both misinformation and various types of countering-misinformation articles. They then answer questions to assess the plausibility and believability of misinformation or counter-misinformation [109]. As an advanced design for this methodology, Orosz et al. [63] ask crowds to first evaluate their initial belief in the misinformation, view the counter-misinformation, and then reevaluate their belief. The change in belief serves as a measure of the effectiveness of counter-misinformation. In-lab experiments investigate diverse countering strategies, including the impact of news sources, both mainstream and private [49], and other factors [4, 10, 25, 41, 43, 51, 53, 68, 80, 86, 87, 92].

Interviews offer personal interactions for crowds to engage in conversations and ask open-ended questions about effective strategies for countering misinformation. During the COVID-19 pandemic in 2020, Borah et al. [11] interviewed young adults and active social media users regarding their COVID-19 perceptions, coping strategies, and recommended

⁵Some reviewed papers use the term questionnaire. In this work, we use "survey" to cover questionnaire- as well as survey-based methodologies.

countermeasures. Findings advocate calling out people sharing misinformation and bringing up media literacy programs to combat misinformation.

Finally, online **surveys** efficiently expand sample sizes and enhance inclusivity and accessibility for geographically dispersed or busy participants, thereby complementing in-lab experiments and interviews. These surveys collect demographic information and gather crowd opinions on misinformation and counter-misinformation, including how individuals handle potential false posts [43] and their evaluations of countering efforts [40].

5.1.2 Indirect Assessment. In contrast to direct assessment, indirect assessment utilizes proxy metrics to measure the effectiveness of counter-misinformation messages in a data-driven manner. For instance, Zhang et al. [111] analyze the **sentiment** in the comments and replies of the crowds to counter-misinformation messages on Sina Weibo, and use it as an indicator of the efficacy of counter-misinformation messages. Similarly, other works assess the **stance** expressed in comments on fake news rebuttals as a proxy for countering acceptance [102, 103]. They categorize stances as supporting, denying, questioning, and commenting, and define the normalized combined distribution of denying and supporting stances among all comments as the debunking effectiveness index to indicate countering effectiveness [102]. Additionally, Chen et al. [17] use the **number of shares** of fact-checks as a proxy for the efficacy of certain fact-checks. They explore the influence of peripheral and central cues on fact-check shares, observing that stronger effects lead to higher shares.

5.2 Findings from Effective Counter-Misinformation

After establishing the appropriate crowd-based evaluation methods, we utilize crowd evaluators to gain comprehensive insights into the effectiveness of counter-misinformation efforts. Specifically, we aim to uncover the underlying factors contributing to these endeavors, considering dimensions such as media formats, content traits, communication styles, audience-related factors, countering order, and word placement.

- 5.2.1 Media Formats. We examine the impacts of different formats employed in counter-misinformation efforts. The predominant format is to respond to textual misinformation with text-based countermeasures [43, 93, 108, 109]. Furthermore, a study by Vraga et al. [98] explored text-based responses to video misinformation on health topics. Crowd evaluators viewed misinformation videos and accompanied debunking comments. The result showed that real-time crowd debunking in text partially reduced belief in misinformation (p < 0.01). Additionally, Kessler and Bachmann [40] investigated text and images, finding credible text-based debunking supported by evidence effectively countered misinformation, while images alone had limited impact. Moreover, Masullo and Kim [52] studied uncivil countering comments with emojis, discovering that while the uncivil countering text has effects on the perception of the credibility of the news stories, reactions like "angry" can mitigate incivility and reduce dislike of news or comments, especially across different political leanings (p < 0.01). This finding potentially indicates the efficacy of emojis when countering misinformation. Meanwhile, Pasquetto et al. [67] found that audio-based corrections on WhatsApp platforms generate more interest and are more effective than text- or image-based messages in countering misinformation (p = 0.01).
- 5.2.2 Content Traits. We further delve into the key content characteristics that are crucial to effectively countering misinformation. These include the ability to uncover the motivations behind misinformation [83], the use of evidence-based and logical counter-arguments [63, 102], the inclusion of warnings to alert readers to potential misinformation [43], and the careful selection of credible sources for correction [109], which are elaborated on below.

Regarding **revealing misinformation motives**, Stojanov [83] examined the impact of debunking messages that reveal the motives behind conspiracy theories, particularly in the context of countering vaccine-related medical conspiracy theories. Their findings suggest that revealing the motives of conspiracy theories can effectively reduce belief in medical conspiracy theories (p < 0.05), although the effect on belief in general conspiracy theories is less clear.

Regarding **supporting claims with evidence**, Wang et al. [102] highlighted the importance of citing evidence to enhance the debunking effect, which is better than debunking methods with uncited evidence (p < 0.001). Subsequently, Kessler and Bachmann [40] extended these findings by confirming that credible debunking text (rather than images) with evidence is effective in countering misinformation (p < 0.001). Another related aspect involves **logical counter-arguments**. Orosz et al. [63] presented subjects with conspiracy theory statements alongside countering posts containing rational counter-arguments. They found that this approach was effective in reducing belief in conspiracy theories ($p \le 0.01$). Additionally, pointing out the fallacies in the reasoning behind the original misinformation post, as demonstrated by Stojanov [83], was also effective in reducing belief in medical conspiracy theories.

Regarding **displaying warning messages**, Kirchner and Reuter [43] revealed that German adults have a strong preference for displaying warnings on inaccurate posts as a strategy to combat fake news (65% agreement compared to the baseline of 51-57%). Crowd evaluators also stressed the importance of social media platforms providing explanations for flagged misinformation (71% agreement compared to the baseline of 51-57%). In summary, warning-based approaches have demonstrated significant effectiveness in reducing the believability of fake news, particularly when accompanied by explanatory text.

Lastly, when **selecting correction sources**, researchers have identified variations in the persuasiveness of different sources, particularly considering that the impact of corrections can vary across different societies. For example, Yu et al. [109] highlighted that in authoritative societies, corrections from government sources tend to have greater credibility than those from professionals or laypeople ($p \le 0.05$). This underscores the need to tailor correction strategies and source selection to specific societal contexts.

5.2.3 Communication Styles. Analyzing different communication styles of counter-misinformation, such as humorous and uncivil responses, provides an additional dimension to evaluating its effectiveness. Regarding humor, researchers have explored the potential of humor in correcting misinformation. For example, Kim et al. [41] investigated the impact of humorous versus non-humorous corrective messages in countering misinformation about the HPV vaccine. The study found that when correcting misinformation with humor, crowds' visual attention increased towards the image portion of the counter-misinformation contents, indirectly reducing HPV misperceptions when measured by the reduced credibility of the misinformation. Regarding uncivil responses, Masullo and Kim [52] investigated the effect of uncivil counter-misinformation comments on readers' attitudes and perceptions. In an online survey, crowd evaluators were exposed to misinformation articles, uncivil comments, and corresponding social reactions to the comments, followed by questions about their feelings. The findings revealed that while uncivil counter-comments influenced how readers viewed the comments and the commentators themselves, they did not affect the credibility of the underlying articles. This suggests that uncivil responses may not contribute significantly to countering misinformation.

In addition, the literature has explored other factors such as **ridiculing vs. empathetic**, **readability**, and **tone of correction**. According to Orosz et al. [63], ridiculing arguments effectively reduce belief in conspiracy theories, while empathetic counterarguments have no significant impact on belief in misinformation. Wang et al. [103] investigated the impact of the readability of the rebuttal text on crowds' acceptance of the rebuttal. The study found that higher readability positively influenced users' acceptance of the rebuttal. Improved readability indicates that users can easily

understand and absorb the rebuttal, thereby enhancing its effectiveness. Lastly, Yu et al. [109] examined the impact of the tone of corrective messages on the believability of the correction. The research indicated that a formal tone was more believable than a less formal and conversational tone.

5.2.4 Audience Factors. In addition to the inherent characteristics of counter-misinformation, a number of external factors related to the audience, including media literacy, cognitive capability, political stance, trust in media, and concern about misinformation, also have an impact on its effectiveness.

Research has extensively explored the impact of **media literacy** on the perception of misinformation. For instance, Tanihara et al. [88] found that crowd evaluators with lower levels of media literacy are more likely to change their perceptions of misinformation when exposed to corrective messages. In a study conducted by Wang et al. [103], **cognitive capability** was assessed based on an individual's language-related cues, including vocabulary size. The findings revealed that crowd evaluators with lower cognitive capabilities tend to rely on the credibility of the source and the quality of the argument in the rebuttal text to accept it. On the other hand, readers with high cognitive capability have a greater demand for greater readability, even when the sources and arguments are solid.

Regarding **political stance**, Pasquetto et al. [67] found that the correction from people with strong ties (e.g., the same political stance) can lead crowds to more actively re-share these debunks and counter misinformation. This tendency was corroborated by Yang and Overton [108], who observed that crowd evaluators are more likely to accept corrections from sources that align with their existing attitudes. Regarding **trust in media**, Primig [71] discovered that greater trust in media sources corresponds to higher believability in fact-checking sources and messages, especially when combined with trust in politics. Conversely, for social corrections on social media platforms, Yang and Overton [108] noted their effectiveness is more pronounced among users who experience higher levels of uncertainty on these platforms. Regarding **concern about misinformation**, Yang and Overton [108] found that social corrections work better among users who are more concerned or worried about the potential harm caused by misinformation on social media platforms.

5.2.5 Countering Order and Word Placement. Researchers have also examined other less prominent factors such as the order of counter-misinformation and the placement of negation. Regarding countering order, two contrasting approaches emerge: debunking starts by presenting misinformation and then offers a counterresponse, while prebunking reverses this order by introducing counter-misinformation as a preemptive warning or reminder. Dai et al. [22] confirmed that prebunking messages, especially when combined with fact-checks or inoculation messages, effectively made crowd evaluators more skeptical of misinformation. Additionally, Tay et al. [89] conducted a more comprehensive evaluation that extended beyond traditional questionnaires to assess user behaviors, such as information seeking and the promotion of online misinformation. The results highlighted the effectiveness of both prebunking and debunking in reducing belief in misinformation.

Another nuanced aspect studied is how the **placement of negation** during debunking impacts crowd memory and, consequently, the effectiveness of debunking [69]. In social media, brief affirmations or negations are often used to clarify claims. In this context, Pillai et al. [69] found that when crowd evaluators encounter negated messages (e.g., "This is wrong."), they often remember the main claim but forget the negative part. They tested placing the negation before or after the entire claim and found that both methods were equally memorable. This result highlights the possibility of diverse approaches to conveying affirmations and negations.

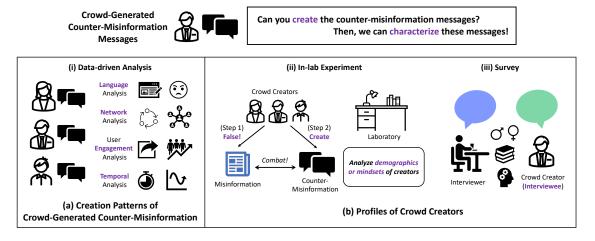


Fig. 6. Illustration of crowds' role as creators of counter-misinformation.

6 CROWDS AS CREATORS OF COUNTER-MISINFORMATION

In addition to serving as annotators and evaluators, crowds have the ability to create their own counter-misinformation messages on social media platforms. In this section, we aim to examine their role as content creators (see Figure 6) to investigate their unique perspective and proactive involvement in combating misinformation while characterizing their content. To achieve this goal, we first present three characterization methods that measure how crowds actively combat misinformation as creators. These methods are: data-driven analysis, in-lab experiment, and survey (see Table 7-(a)). Based on these methods, we discuss findings on analyzing counter-misinformation generated by crowds, with a specific focus on creation patterns and creator profiles (see Tables 7-(b) and (c)). Specifically, we conduct a comprehensive examination of counter-misinformation generated by crowds, revealing the creation patterns of counter-misinformation. Finally, we explore the intricate dynamics of the human elements involved, focusing on the profiles of crowd creators.

6.1 Characterization Methods

To establish a comprehensive framework for analyzing the active counter-misinformation creation process involving human elements, we present three characterization methods in Table 7-(a). We note that different methods have been utilized depending on what we aim to characterize. First, researchers mainly rely on data-driven analysis to understand the **creation patterns** of effective crowd-generated counter-misinformation. In a nutshell, they begin by crawling large-scale crowd-generated data, including posts and social network relationships. This data is then examined from different perspectives, such as language patterns, networks, and temporal trends [3, 27, 36, 42, 57, 64, 107], which will be elaborated in Section 6.2.

On the other hand, researchers employ a combination of in-lab experiments and surveys to study **creator profiles**. For in-lab experiments [21, 35, 37, 65, 66, 85, 93], crowd creators are exposed to misinformation text and then asked to respond by either countering or endorsing it. In the meantime, researchers collect information on creators, including their political leanings and beliefs related to misinformation, in order to analyze their attributes. Additionally, researchers conduct online surveys to assess the creators' levels of belief in misinformation and collect demographic information, including their media competency [16]. The results are discussed in Section 6.3.

Table 7. Taxonomy of crowd creators for analyzing crowd-generated counter-misinformation.

		Categories	References
(a) Methods	Creation Patterns	Data-driven Analysis	[3, 27, 36, 42, 57, 64, 107]
	Creator Profiles	In-lab Experiment Survey	[21, 35, 37, 65, 66, 85, 93] [16]
(b) Creation Patterns	Language	Sentiment Emotion Psycholinguistic Features URL Hashtag Others	[3, 57] [42, 57, 107] [27, 57, 107] [36, 57, 64] [7, 29] [15, 62, 113]
	Network	Network Co-existence Pattern Information Transmission User Connectivity Pattern	[29] [113] [2, 18]
	User Engagement	Post Volume Post Sharing	[57, 101] [20, 57]
	Temporal	Temporal Trend Life Cycle	[29] [113]
(c) Creator Profiles	Demographics	Age and Education Political Ideology Media Literacy	[95] [21, 81] [35, 37, 93, 95]
	Mindsets	Sharing Denials Others' Susceptibility Third-person Effect Harm Awareness	[65, 66] [85] [16] [95, 112]

The goal of these methods is to characterize the creators themselves and uncover the patterns and attributes associated with crowd-generated counter-misinformation. In this context, it is important to note that this objective contrasts with the goal of the crowd-based evaluation methods, which assess misinformation countermeasure effectiveness.

6.2 Creation Patterns

In the battle against misinformation, crowds actively contribute by generating a multitude of content that includes debunking posts and responses. A significant amount of research has directed its attention towards comprehending how such counter-misinformation messages are crafted and pinpointing the patterns they contain [20, 42, 57, 62]. Researchers typically first manually label sampled text and visuals into categories such as misinformation and counter-misinformation, and then train classifiers for extensive categorization on unlabeled data points due to the high cost of manual labeling. This comprehensive categorization serves as the basis for analyzing counter-misinformation, including content characteristics, network dynamics, temporal aspects, and social media engagement. For a detailed breakdown of these dimensions, refer to Table 7-(b).

6.2.1 Language Analysis. Crowd-generated counter-misinformation messages exhibit distinct language patterns when compared to other online content [3, 42, 107]. We summarize these patterns through various aspects, including sentiments, emotions, psycholinguistic features, and textual components like URLs and hashtags.

First, **sentiment** analysis revealed differences among various topics. For instance, during the COVID-19 pandemic, positive attitudes were expressed in comments countering COVID-19 conspiracy theories on Facebook [3], while countermisinformation tweets regarding fake COVID-19 cures were more neutral [57]. In addition, **emotions** expressed in counter-misinformation have been explored in various contexts, demonstrating that contexts affect different emotional responses. For instance, Xue et al. [107] used IBM Watson Tone Analyzer to extract emotions, revealing that COVID-19 vaccine fact-checking posts on Facebook tended to maintain a neutral tone, while public comments often displayed more emotionally charged responses. Additionally, Kim and Chen [42] analyzed emotions in videos related to COVID-19 on YouTube. They utilized the NRC Emotion Lexicon⁶, which contains a list of English words and their associations with emotions and sentiments. The study identified two emotional dimensions, trust and fear, and observed differential utilization of these emotions in debunking videos.

Furthermore, researchers have delved into the **psycholinguistic features** of counter-misinformation using tools such as Linguistic Inquiry and Word Count (LIWC) or IBM Watson Tone Analyzer [27, 57, 107]. For instance, on Facebook, posts fact-checking COVID-19 vaccine information exhibited higher levels of confidence compared to general public posts [107]. Additionally, Giachanou et al. [27] discovered that crowds tend to employ more positive language and causal language, whereas misinformation spreaders often use more informal language.

Additionally, two noteworthy elements frequently integrated into counter-misinformation messages are URLs and hashtags. Uniform Resource Locators (URLs) serve as sources of evidence-based resources [57], often cited in tweets that counter rumors [64]. Moreover, URLs have proven effective in disseminating information for debunking during disaster events, often citing news agencies as their primary information sources [36]. Hashtags, on the other hand, are employed to enhance the visibility and categorization of content. For example, Gunaratne et al. [29] analyzed vaccine-related tweets and found that 86% of users exclusively used pro-vaccine hashtags, while 12% opted for anti-vaccine hashtags. Additionally, Babcock et al. [7] found that the hashtag "#fakenews" was widely used to attack fake news.

Besides these specific content attributes, **other dimensions** like stance [113], user impression [62], politeness [57], and the group identity language [15] have also been examined in counter-misinformation.

6.2.2 Network Analysis. Researchers employ various network analysis approaches and tools (e.g., NodeXL and Gephi [8, 23, 26, 39, 55, 105]) to uncover the intricate interplay between misinformation/counter-misinformation information flow and user connections on social media platforms. The representative approaches encompass patterns of co-existence in networks, post sharing/(re)tweeting, and connectivity of users.

Regarding **network co-existence patterns**, Gunaratne et al. [29] examined the co-occurrence of anti-vaccine and pro-vaccine hashtags on Twitter. Their analysis involved constructing a network with hashtags as nodes and co-occurring hashtags as edges, revealing distinct community structures within both pro-vaccine and anti-vaccine hashtags. The results highlighted that pro-vaccine hashtags formed a dominant community along with a few closely connected sub-communities. Conversely, anti-vaccine hashtags largely converged into one community with a smaller, remote sub-community that focuses on specific vaccines. This analysis enhanced our understanding of the discourse and inter-relationship between misinformation and counter-misinformation.

 $^{^{6}} http://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm \\$

To investigate **information transmission** within a social network, Zubiaga et al. [113] investigated the rumor (re)tweeting networks which included three types of retweets: (1) unverified source tweets, (2) accurate tweets supporting true information or denying false rumors (i.e., counter-misinformation), and (3) inaccurate tweets denying true information or supporting false rumors (i.e., misinformation). By examining retweeting relationships between (re)tweet nodes, they discovered that retweets of accurate tweets were primarily observed in certain misinformation topics, such as the Ottawa shooting and the Sydney siege. In contrast, tweets sharing unverified rumors had a broader spread across different topics.

User connectivity patterns on social network platforms such as Twitter have also been studied in the literature [2, 18]. For instance, during the COVID-19 pandemic on Twitter, Ahmed et al. [2] regarded crowds as nodes and the "reply-to" or "mention" relationships in tweets as edges in a graph. A "self-loop" relationship is added in the graph if there is no "reply-to" or "mention" in the tweets. By analyzing such a graph, researchers found that 32.2% of the crowds denounced the COVID-19 5G conspiracy theory. They also identified the two largest network structures, consisting of an isolated group and a broadcast group. The results revealed that there was a lack of an active authority figure to counter the spread of misinformation. Instead, the crowds countered the conspiracy theory with widespread denouncement. Similarly, Chiu et al. [18] considered the "mention," "retweet," and "self-loop" relationships between users to create the graph and conduct the cluster analysis, while focusing on the diffusion scope, speed, and shape for true and fake news across the users. They also tested whether the attributes of the true or fake news spreaders would affect the aforementioned three metrics. The results showed that true news from the crowd tended to spread later and with less broadcast influence compared to fake news. In addition, Wang et al. [101] investigated the follower-followee relationships of refuters and non-refuters. They developed a deep-learning-based text classifier to identify debunked and non-debunked posts on Sina Weibo. They then identified associated refuters and non-refuters whose follower-followee networks are crawled as well. Their analysis unveiled that nodes with greater centrality had more follower-followee edges, and weakly connected components could easily disseminate both debunked and non-debunked posts. This suggests that misinformation and counter-misinformation have similar propagation patterns, considering that both can spread from weekly-connected nodes.

6.2.3 User Engagement Analysis. Social media engagement analysis explores how crowds interact with online posts containing both misinformation and counter-misinformation. These interactions can be measured through metrics like post volume growth, and sharing behaviors can differ depending on specific scenarios.

For example, Wang et al. [101] observed that the **post volumes** of counter-misinformation exhibited growth rates similar to those containing misinformation. Nonetheless, Micallef et al. [57] uncovered disparities in their absolute quantities and growth trends during the COVID-19 pandemic. Specifically, the number of counter-misinformation posts was significantly lower than the number of misinformation posts. Apart from post volumes, they also analyzed the imbalanced **sharing behavior** associated with these posts, and found that the majority of posts, regardless of their classification as misinformation or counter-misinformation, received minimal to no shares. However, specific situations could lead to variations. For example, when examining the rumored death of Singapore's President Lee Kuan Yew, Chua et al. [20] found that tweets aiming to correct the rumor garnered more frequent retweets than the initial rumor tweets. This suggests that, in certain contexts, counter-misinformation may be more prone to be shared than misinformation.

6.2.4 Temporal Analysis. Temporal analysis aims to uncover evolving misinformation and counter-misinformation traits by studying temporal trends and life cycle patterns, offering valuable insights into their dynamics.

For instance, Gunaratne et al. [29] examined the **temporal trends** of disease cases, pro-vaccine of diseases, and anti-vaccine of diseases tweets, as well as the crowds who tweeted between 2010 and 2019. The results revealed that pro-vaccine tweets consistently outpaced anti-vaccine tweets in volume, and this trend continued to increase over time. Similarly, Zubiaga et al. [113] conducted a study on the **life cycle** of rumors and their countering. They aimed to understand how users engage with rumors, in terms of both their spread and debunking, before and after the veracity of the rumor is confirmed. Through manual identification and annotation of rumor threads, interesting observations were made. Notably, rumors that were eventually proved to be true, were debunked more quickly than false rumors. Interestingly, when a rumor tweet was countered by either the crowd or an organization, retweets occurred more evenly over time, indicating sustained retweeting activities. These findings shed light on the dynamics of rumor propagation and debunking activities over time.

6.3 Creator Profiles

Beyond characterizing the creation patterns of crowd-generated counter-misinformation, we also analyze the profiles of these crowds as counter-misinformation creators. Specifically, we examine their demographic factors and mindsets, as outlined in Table 7-(c).

6.3.1 Demographics. Literature highlights the significant influence of certain demographic factors on crowds' willingness and involvement in countering misinformation. One noteworthy aspect is **political ideology**, which influences one's approach to governance and public policy. According to Cohen et al. [21], the presence of a social identity threat in fake news content related to one's political ingroup indirectly affects crowds' readiness to publicly denounce fake news articles. This threat attacks or undermines their group's social standing and political ideology. Similarly, Steinfeld [81] found that individuals who engage in violent or illegal political protests tend to actively combat disinformation, even though they may occasionally share disinformation themselves. These findings underscore the intricate interplay between political ideology and countering misinformation.

Media literacy, also known as "Information Literacy Competence" and "News Media Literacy," is another widely investigated factor. It involves the critical analysis of media content, particularly news, to discern its credibility, bias, and intention. Several studies have highlighted its absence among the general audience, as well as the necessity for improved media literacy education. For instance, Igbinovia et al. [37] emphasized the importance of media literacy in limiting the spread of fake news during the COVID-19 pandemic. They revealed that greater media literacy can aid in identifying fake news, which in turn may facilitate social correction [95].

Meanwhile, a concerning lack of media literacy has been observed. Veeriah [93] affirmed the crucial role of media literacy in motivating corrective responses to misinformation. However, they found that even young crowds who felt sure about identifying fake news still demonstrated only moderate levels of media literacy. This observation implies the necessity of initiating media literacy education amongst young crowds to bolster the fight against fake news. Similarly, Huber et al. [35] echoed this finding, indicating that relying solely on general media literacy is insufficient in effectively countering certain types of fake news. These collective findings highlight the significance of high-level or even specialized media literacy for crowds engaged in countering misinformation.

In addition to political ideology and media literacy, the above studies also examined additional factors such as **age** and **education**. For instance, Vijaykumar et al. [95] found that crowds who are younger or less educated tend to be less involved in countering misinformation.

6.3.2 Mindsets. The motivations of crowds to counter misinformation are influenced by their beliefs and mindsets. For instance, the act of **sharing denials** has been identified as a crucial strategy for countering misinformation [65, 66]. Pal et al. [65, 66] delved into this area and identified three key beliefs that encourage crowds to share messages that deny rumors: (1) the belief that sharing denials helps spread the truth, (2) the belief that friends and the online community would favor the behavior of sharing rumor denials, and (3) the belief that the credibility of the source of rumor denials encourages sharing, thus influencing crowds' willingness to share for countering.

Moreover, we note the presence of the phenomenon known as the **third-person effect**, denoting the belief among individuals that media messages have a greater influence on others than on themselves. For instance, Chen and Fu [16] found that this effect positively encourages crowds to debunk online misinformation. Another related belief, known as the "**others' susceptibility**", refers to the perception that "others will be affected by or susceptible to misinformation". Sun et al. [85] discovered that such belief in others' susceptibility can induce negative emotions such as guilt and anger, thus motivating vaccine supporters to correct anti-vaccination misinformation actively.

Lastly, harm awareness, or being aware of the negative consequences, can also motivate efforts to counter misinformation. For example, Zhao et al. [112] found that perceiving the harm caused by rumors predicts a significant increase in engagement to counter misinformation. Similarly, Vijaykumar et al. [95] discovered that when crowds perceive that the severity of COVID-19 is not being properly addressed, they are motivated to take action against related misinformation.

7 FUTURE DIRECTIONS

In this section, we outline potential avenues for future research in this field:

- Improving Crowd Annotations: While collaborative labeling aims to overcome the limitations in individual labeling (e.g., individual annotation biases [58]), it's important to note that individuals often share similar perspectives (homophily). Therefore, it's unclear whether collaborative labeling effectively captures diverse viewpoints. Future research should explore this aspect and develop strategies to encourage diversity within groups countering misinformation. Similarly, crowd-in-the-loop identification of misinformation can benefit from agile classifiers that do not require extensive labeled examples initially and can quickly adapt to emerging misinformation [60]. One approach to achieve this is by utilizing few-shot learning techniques [60].
- Multi-platform and Multimodal Countering: Current social media-related work predominantly focuses on one specific platform like Twitter [19, 20, 34], Facebook [107], and Sina Weibo [103]. However, crowds countering misinformation may behave differently across various platforms due to variations in user demographics and engagement dynamics. Exploring how crowds counter on multiple platforms and whether countering on one platform influences others is essential for a comprehensive understanding of crowd-driven misinformation mitigation. Additionally, the crowd-generated counter-misinformation isn't limited to text alone; it can also involve the use of images or videos to enhance the persuasiveness of their debunking efforts. Investigating these multimodal aspects benefits the design of effective countering contents.
- Multilingual and Topic-specific Countering: Most research works concentrate on either a single language
 (e.g., English [19] or Chinese [103]) or a specific misinformation topic (e.g., COVID-19 [93]). But, misinformation
 spans across languages and topics, leading to diverse countering actions. Analyzing how crowds in underrepresentative languages combat various topics reveals variations in countering strategies across languages
 and topics, thus contributing to a comprehensive understanding of misinformation countering. On the other

hand, existing research on the profiles of crowds focuses on demographic factors such as education, political leanings, and media literacy. However, it overlooks misinformation topic-specific factors. For instance, an individual having a background in health education may be effective at countering health misinformation but susceptible to believing in climate misinformation. Therefore, exploring these topic-specific factors can enhance our understanding of human factors involved in countering misinformation.

• In-thread Countering: While current research primarily examines the impact of standalone or accompanied counter-misinformation messages on social media platforms [20, 107], there is limited exploration into the dynamics of counter-misinformation within conversations or threads. For example, a crucial question arises: "When others in a thread engage in countering, does it lead to correcting the misinformation or, conversely, amplifying it?" This form of in-thread countering (e.g., counter-misinformation responses to original misinformation posts) is frequently observed on social media platforms like Twitter and Reddit [1]. Its impact is amplified due to the active engagement of multiple users in the thread. Investigating these in-thread behaviors provides valuable insights into the dynamics of countering and offers guidance for the design of effective counter-misinformation strategies.

8 CONCLUSIONS

While crowd-based efforts to combat misinformation have increasingly attracted attention, there has yet to be a comprehensive survey paper that examines the multifaceted roles of crowds. Our study fills this gap by systematically categorizing the three primary roles of crowds: annotators, evaluators, and creators. Toward this end, we present the inaugural systematic survey of 88 papers investigating crowd-based efforts, which were collected by following PRISMA guidelines. Specifically, we presented key data statistics on misinformation, counter-misinformation, and crowd inputs found in the literature. Additionally, we proposed a novel taxonomy that covers the diverse roles of crowds in a comprehensive way. Moreover, we provide detailed insights and findings extracted from the surveyed papers, offering valuable resources for effective counter-misinformation. By doing so, this survey helps readers grasp the latest research developments in this field and establishes the foundation for encouraging advanced crowd-assisted methodologies to combat misinformation.

REFERENCES

- [1] Vlad Achimescu and Pavel Dimitrov Chachev. 2020. Raising the Flag: Monitoring User Perceived Disinformation on Reddit. Information 12 (12
- [2] Wasim Ahmed, Josep Vidal-Alaball, Joseph Downing, and Francesc López Seguí. 2020. COVID-19 and the 5G Conspiracy Theory: Social Network Analysis of Twitter Data. Journal of Medical Internet Research 22 (5 2020), e19458. Issue 5.
- [3] Mohammad A. Al-Motlaq. 2021. "There is No Corona; It's a Conspiracy": Addressing the Perceptions of People about COVID-19 through the Narrative of Their Comments on Social Media. Journal of Consumer Health on the Internet 25 (1 2021), 65–76. Issue 1.
- [4] Jennifer Allen, Antonio A. Arechar, Gordon Pennycook, and David G. Rand. 2021. Scaling up fact-checking using the wisdom of crowds. Science Advances 7 (9 2021). Issue 36.
- [5] Jennifer Allen, Cameron Martel, and David G Rand. 2022. Birds of a feather don't fact-check each other: Partisanship and the evaluation of news in Twitter's Birdwatch crowdsourced fact-checking program. In CHI Conference on Human Factors in Computing Systems. 1–19.
- [6] Ahmer Arif, John J. Robinson, Stephanie A. Stanek, Elodie S. Fichet, Paul Townsend, Zena Worku, and Kate Starbird. 2017. A closer look at the self-correcting crowd: Examining corrections in online rumors. Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing, 155–168.
- [7] Matthew Babcock, David M. Beskow, and Kathleen M. Carley. 2019. Different faces of false: The spread and curtailment of false information in the black Panther Twitter discussion. *Journal of Data and Information Quality* 11 (9 2019), 1–15. Issue 4.
- [8] Matthew Babcock, Ramon Alfonso Villa Cox, and Sumeet Kumar. 2019. Diffusion of pro- and anti-false information tweets: the Black Panther movie case. Computational and Mathematical Organization Theory 25 (3 2019), 72–84. Issue 1.

- [9] Md Momen Bhuiyan, Amy X. Zhang, Connie Moon Sehat, and Tanushree Mitra. 2020. Investigating Differences in Crowdsourced News Credibility Assessment. Proceedings of the ACM on Human-Computer Interaction 4 (10 2020), 1–26. Issue CSCW2.
- [10] Leticia Bode and Emily K. Vraga. 2018. See Something, Say Something: Correction of Global Health Misinformation on Social Media. Health Communication 33 (9 2018), 1131–1140. Issue 9.
- [11] Porismita Borah, Bimbisar Irom, and Ying Chia Hsu. 2021. 'It infuriates me': examining young adults' reactions to and recommendations to fight misinformation about COVID-19. *Journal of Youth Studies* (8 2021), 1–21.
- [12] George Buchanan, Ryan Kelly, Stephann Makri, and Dana McKay. 2022. Reading between the lies: A classification scheme of types of reply to misinformation in public discussion threads. In ACM SIGIR Conference on Human Information Interaction and Retrieval. 243–253.
- [13] Man-pui Sally Chan, Christopher R Jones, Kathleen Hall Jamieson, and Dolores Albarracín. 2017. Debunking: A meta-analysis of the psychological efficacy of messages countering misinformation. Psychological science 28, 11 (2017), 1531–1546.
- [14] Schuldt H. Shabani S. Charlesworth Z., Sokhn M. 2021. SAMS: Human-in-the-loop approach to combat the sharing of digital misinformation. CEUR Workshop Proceedings.
- [15] Kaiping Chen, Yepeng Jin, and Anqi Shao. 2022. Science Factionalism: How Group Identity Language Affects Public Engagement With Misinformation and Debunking Narratives on a Popular Q&A Platform in China. Social Media+ Society 8, 1 (2022), 20563051221077019.
- [16] Liang Chen and Lunrui Fu. 2022. Let's fight the infodemic: the third-person effect process of misinformation during public health emergencies.

 Internet Research (2022).
- [17] Qiang Chen, Yangyi Zhang, Richard Evans, and Chen Min. 2021. Why do citizens share COVID-19 fact-checks posted by Chinese government social media accounts? The elaboration likelihood model. *International Journal of Environmental Research and Public Health* 18, 19 (2021), 10058.
- [18] Ming Ming Chiu, Chong Hyun Park, Hyelim Lee, Yu Won Oh, and Jeong-Nam Kim. 2022. Election Fraud and Misinformation on Twitter: Author, Cluster, and Message Antecedents. *Media and Communication* 10, 2 (2022), 66–80.
- [19] Alton Y. K. Chua and Snehasish Banerjee. 2017. A Study of Tweet Veracity to Separate Rumours from Counter-Rumours. Proceedings of the 8th international conference on social media & society, 1–8.
- [20] Alton Y. K Chua, Cheng-Ying Tee, Augustine Pang, and Ee-Peng Lim. 2017. The Retransmission of Rumor and Rumor Correction Messages on Twitter. American Behavioral Scientist 61 (6 2017), 707–723. Issue 7.
- [21] Elizabeth L. Cohen, Anita Atwell Seate, Stephen M. Kromka, Andrew Sutherland, Matthew Thomas, Karissa Skerda, and Andrew Nicholson. 2020. To correct or not to correct? Social identity threats increase willingness to denounce fake news through presumed media influence and hostile media perceptions. Communication Research Reports 37 (10 2020), 263–275. Issue 5.
- [22] Yue Nancy Dai, Wufan Jia, Lunrui Fu, Mengru Sun, and Li Crystal Jiang. 2022. The effects of self-generated and other-generated eWOM in inoculating against misinformation. Telematics and Informatics 71 (2022), 101835.
- [23] Anh Dang, Michael Smit, Abidalrahman Moh'd, Rosane Minghim, and Evangelos Milios. 2016. Toward understanding how users respond to rumours in social media. 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), 777–784.
- [24] Munaza Farooq, Aqsa Ashraf Makhdomi, and Iqra Altaf Gillani. 2022. Crowd Sourcing and Blockchain-Based Incentive Mechanism to Combat Fake News. In Combating Fake News with Computational Intelligence Techniques. Springer, 299–325.
- [25] Jieyu Ding Featherstone and Jingwen Zhang. 2020. Feeling angry: the effects of vaccine misinformation and refutational messages on negative emotions and vaccination attitude. Journal of Health Communication 25 (9 2020), 692–702. Issue 9.
- [26] Claudia Flores-Saviaga and Saiph Savage. 2021. Fighting disaster misinformation in Latin America: the #19S Mexican earthquake case study. Personal and Ubiquitous Computing 25 (4 2021), 353–373. Issue 2.
- [27] Anastasia Giachanou, Bilal Ghanem, Esteban A Rissola, Paolo Rosso, Fabio Crestani, and Daniel Oberski. 2022. The impact of psycholinguistic patterns in discriminating between fake news spreaders and fact checkers. Data & Knowledge Engineering 138 (2022), 101960.
- [28] Dion Hoe-Lian Goh, Alton Y.K. Chua, Hanyu Shi, Wenju Wei, Haiyan Wang, and Ee Peng Lim. 2017. An Analysis of Rumor and Counter-Rumor Messages in Social Media. , 256-266 pages.
- [29] Keith Gunaratne, Eric A. Coomes, and Hourmazd Haghbayan. 2019. Temporal trends in anti-vaccine discourse on Twitter. Vaccine 37 (8 2019), 4867-4871. Issue 35
- [30] Bin Guo, Yasan Ding, Lina Yao, Yunji Liang, and Zhiwen Yu. 2019. The future of misinformation detection: new perspectives and trends. arXiv preprint arXiv:1909.03654 (2019).
- [31] Katrin Hartwig, Frederic Doell, and Christian Reuter. 2023. The Landscape of User-centered Misinformation Interventions—A Systematic Literature Review. arXiv preprint arXiv:2301.06517 (2023).
- [32] Bing He, Mustaque Ahamad, and Srijan Kumar. 2021. Petgen: Personalized text generation attack on deep sequence embedding-based classification models. In Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining. 575–584.
- [33] Bing He, Mustaque Ahamad, and Srijan Kumar. 2023. Reinforcement learning-based counter-misinformation response generation: a case study of COVID-19 vaccine misinformation. In Proceedings of the ACM Web Conference 2023. 2698–2709.
- [34] Bing He, Caleb Ziems, Sandeep Soni, Naren Ramakrishnan, Diyi Yang, and Srijan Kumar. 2021. Racism is a virus: Anti-Asian hate and counterspeech in social media during the COVID-19 crisis. In *Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*. 90–94.
- [35] Brigitte Huber, Porismita Borah, and Homero Gil de Zúñiga. 2022. Taking corrective action when exposed to fake news: The role of fake news literacy. *Journal of Media Literacy Education* 14, 2 (2022), 1–14.

- [36] Kyle Hunt, Bairong Wang, and Jun Zhuang. 2020. Misinformation debunking and cross-platform information sharing through Twitter during Hurricanes Harvey and Irma: a case study on shelters and ID checks. *Natural Hazards* 103 (8 2020), 861–883. Issue 1.
- [37] Magnus Osahon Igbinovia, Omorodion Okuonghae, and John Oluwaseye Adebayo. 2021. Information literacy competence in curtailing fake news about the COVID-19 pandemic among undergraduates in Nigeria. Reference Services Review 49 (5 2021), 3–18. Issue 1.
- [38] Md Rafiqul Islam, Shaowu Liu, Xianzhi Wang, and Guandong Xu. 2020. Deep learning for misinformation detection on online social networks: a survey and new perspectives. Social Network Analysis and Mining 10 (2020), 1–20.
- [39] Anna-Katharina Jung, Björn Ross, and Stefan Stieglitz. 2020. Caution: Rumors ahead—A case study on the debunking of false information on Twitter. Big Data & Society 7 (7 2020), 205395172098012. Issue 2.
- [40] Sabrina Heike Kessler and Eva Bachmann. 2022. Debunking health myths on the internet: the persuasive effect of (visual) online communication. Journal of Public Health (2022), 1–13.
- [41] Sojung Claire Kim, Emily K. Vraga, and John Cook. 2021. An Eye Tracking Approach to Understanding Misinformation and Correction Strategies on Social Media: The Mediating Role of Attention and Credibility to Reduce HPV Vaccine Misperceptions. Health Communication 36 (11 2021), 1687–1696. Issue 13.
- [42] Sang Jung Kim and Kaiping Chen. 2022. The use of emotions in conspiracy and debunking videos to engage publics on YouTube. New Media & Society (2022), 14614448221105877.
- [43] Jan Kirchner and Christian Reuter. 2020. Countering Fake News: A Comparison of Possible Solutions Regarding User Acceptance and Effectiveness. Proceedings of the ACM on Human-Computer Interaction 4 (10 2020), 1–27. Issue CSCW2.
- [44] Neta Kligler-Vilenchik. 2022. Collective social correction: addressing misinformation through group practices of information verification on WhatsApp. *Digital Journalism* 10, 2 (2022), 300–318.
- [45] Klaus Krippendorff. 2011. Computing Krippendorff's alpha-reliability. (2011).
- [46] Jiyoung Lee, Shaheen Kanthawala, Brian C. Britt, Danielle F. Deavours, and Tanya Ott-Fulmore. 2021. Prevalence of anger, engaged in sadness: engagement in misinformation, correction, and emotional tweets during mass shootings. Online Information Review ahead-of-print (8 2021). Issue ahead-of-print.
- [47] Zongmin Li, Qi Zhang, Yuhong Wang, and Shihang Wang. 2020. Social media rumor refuter feature analysis and crowd identification based on XGBoost and NLP. Applied Sciences 10, 14 (2020), 4711.
- [48] Yingchen Ma, Bing He, Nathan Subrahmanian, and Srijan Kumar. 2023. Characterizing and Predicting Social Correction on Twitter. In Proceedings of the 15th ACM Web Science Conference 2023. 86–95.
- [49] Moreno Mancosu and Federico Vegetti. 2021. "Is It the Message or the Messenger?": Conspiracy Endorsement and Media Sources. Social Science Computer Review 39 (12 2021), 1203–1217. Issue 6.
- [50] David M Markowitz, Timothy R Levine, Kim B Serota, and Alivia D Moore. 2023. Cross-checking journalistic fact-checkers: The role of sampling and scaling in interpreting false and misleading statements. *Plos one* 18, 7 (2023), e0289004.
- [51] Cameron Martel, Mohsen Mosleh, and David G. Rand. 2021. You're Definitely Wrong, Maybe: Correction Style Has Minimal Effect on Corrections of Misinformation Online. *Media and Communication* 9 (2 2021), 120–133. Issue 1.
- [52] Gina M. Masullo and Jiwon Kim. 2021. Exploring "Angry" and "Like" Reactions on Uncivil Facebook Comments That Correct Misinformation in the News. Digital Journalism 9 (9 2021), 1103–1122. Issue 8.
- [53] Richard McCreadie, Craig Macdonald, and Iadh Ounis. 2015. Crowdsourced Rumour Identification During Emergencies. Proceedings of the 24th International Conference on World Wide Web, 965–970.
- [54] Mary L McHugh. 2012. Interrater reliability: the kappa statistic. Biochemia medica 22, 3 (2012), 276–282.
- [55] Shahan Ali Memon and Kathleen M. Carley. 2020. Characterizing COVID-19 Misinformation Communities Using a Novel Twitter Dataset. (8 2020).
- [56] Nicholas Micallef, Vivienne Armacost, Nasir Memon, and Sameer Patil. 2022. True or false: Studying the work practices of professional fact-checkers. Proceedings of the ACM on Human-Computer Interaction 6, CSCW1 (2022), 1–44.
- [57] Nicholas Micallef, Bing He, Srijan Kumar, Mustaque Ahamad, and Nasir Memon. 2020. The Role of the Crowd in Countering Misinformation: A Case Study of the COVID-19 Infodemic. 2020 IEEE International Conference on Big Data (Big Data), 748–757.
- [58] Tanushree Mitra and Eric Gilbert. 2015. Credbank: A large-scale social media corpus with associated credibility annotations. Ninth international AAAI conference on web and social media.
- [59] David Moher, Alessandro Liberati, Jennifer Tetzlaff, Douglas G Altman, and PRISMA Group*. 2009. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. Annals of internal medicine 151, 4 (2009), 264–269.
- [60] Maximilian Mozes, Jessica Hoffmann, Katrin Tomanek, Muhamed Kouate, Nithum Thain, Ann Yuan, Tolga Bolukbasi, and Lucas Dixon. 2023. Towards Agile Text Classifiers for Everyone. arXiv preprint arXiv:2302.06541 (2023).
- [61] Rohit Mujumdar and Srijan Kumar. 2021. HawkEye: a robust reputation system for community-based counter-misinformation. In Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining. 188–192.
- [62] Akiyo Nadamoto, Mai Miyabe, and Eiji Aramaki. 2013. Analysis of Microblog Rumors and Correction Texts for Disaster Situations. Proceedings of International Conference on Information Integration and Web-based Applications & Services - IIWAS '13, 44–52.
- [63] Gábor Orosz, Péter Krekó, Benedek Paskuj, István Tóth-Király, Beáta Bőthe, and Christine Roland-Lévy. 2016. Changing Conspiracy Beliefs through Rationality and Ridiculing. Frontiers in Psychology 7 (10 2016).

- [64] Anjan Pal, Alton Y.K. Chua, and Dion Hoe-Lian Goh. 2017. Does KFC sell rat? Analysis of tweets in the wake of a rumor outbreak. Aslib Journal of Information Management 69 (11 2017), 660-673. Issue 6.
- [65] Anjan Pal, Alton Y.K. Chua, and Dion Hoe-Lian Goh. 2019. Debunking rumors on social media: The use of denials. Computers in Human Behavior 96 (7 2019). 110–122.
- [66] Anjan Pal, Alton Y. K. Chua, and Dion Hoe-Lian Goh. 2018. Salient Beliefs about Sharing Rumor Denials on the Internet. Proceedings of the 12th International Conference on Ubiquitous Information Management and Communication, 1-7.
- [67] Irene V Pasquetto, Eaman Jahani, Shubham Atreja, and Matthew Baum. 2022. Social Debunking of Misinformation on WhatsApp: The Case for Strong and In-group Ties. Proceedings of the ACM on Human-Computer Interaction 6, CSCW1 (2022), 1–35.
- [68] Gordon Pennycook and David G. Rand. 2019. Fighting misinformation on social media using crowdsourced judgments of news source quality. Proceedings of the National Academy of Sciences 116 (2 2019), 2521–2526. Issue 7.
- [69] Raunak M Pillai, Sarah Brown-Schmidt, and Lisa K Fazio. 2022. Does wording matter? Examining the effect of phrasing on memory for negated political fact checks. Journal of Applied Research in Memory and Cognition (2022).
- [70] Ethan Porter and Thomas J Wood. 2021. The global effectiveness of fact-checking: Evidence from simultaneous experiments in Argentina, Nigeria, South Africa, and the United Kingdom. Proceedings of the National Academy of Sciences 118, 37 (2021), e2104235118.
- [71] Florian Primig. 2022. The Influence of Media Trust and Normative Role Expectations on the Credibility of Fact Checkers. Journalism Practice (2022), 1–21.
- [72] Vartika Pundir, Elangbam Binodini Devi, and Vishnu Nath. 2021. Arresting fake news sharing on social media: a theory of planned behavior approach. Management Research Review 44 (7 2021), 1108–1138. Issue 8.
- [73] Gowri Ramachandran, Daniel Nemeth, David Neville, Dimitrii Zhelezov, Ahmet Yalcin, Oliver Fohrmann, and Bhaskar Krishnamachari. 2020. WhistleBlower: Towards A Decentralized and Open Platform for Spotting Fake News. 2020 IEEE International Conference on Blockchain (Blockchain), 154–161.
- [74] Kevin Roitero, Michael Soprano, Beatrice Portelli, Massimiliano De Luise, Damiano Spina, Vincenzo Della Mea, Giuseppe Serra, Stefano Mizzaro, and Gianluca Demartini. 2021. Can the crowd judge truthfulness? A longitudinal study on recent misinformation about COVID-19. Personal and Ubiquitous Computing (2021), 1–31.
- [75] Shaban Shabani and Maria Sokhn. 2018. Hybrid Machine-Crowd Approach for Fake News Detection. 2018 IEEE 4th International Conference on Collaboration and Internet Computing (CIC), 299–306.
- [76] Karishma Sharma, Feng Qian, He Jiang, Natali Ruchansky, Ming Zhang, and Yan Liu. 2019. Combating fake news: A survey on identification and mitigation techniques. ACM Transactions on Intelligent Systems and Technology 10 (5 2019), 1–42. Issue 3.
- [77] Kai Shu, Deepak Mahudeswaran, Suhang Wang, Dongwon Lee, and Huan Liu. 2020. Fakenewsnet: A data repository with news content, social context, and spatiotemporal information for studying fake news on social media. Big data 8, 3 (2020), 171–188.
- [78] Mohd Ilias M Shuhud, Najwa Hayaati Mohd Alwi, and Azni Haslizan Abd Halim. 2017. Six Critical Processes to Refute Social-Media-Rumor. Advanced Science Letters 23 (5 2017), 4929–4933. Issue 5.
- [79] Craig Silverman. 2016. This analysis shows how viral fake election news stories outperformed real news on Facebook. BuzzFeed news 16 (2016).
- [80] Michael Soprano, Kevin Roitero, David La Barbera, Davide Ceolin, Damiano Spina, Stefano Mizzaro, and Gianluca Demartini. 2021. The many dimensions of truthfulness: Crowdsourcing misinformation assessments on a multidimensional scale. *Information Processing & Management* 58 (11 2021), 102710. Issue 6.
- [81] Nili Steinfeld. 2022. The disinformation warfare: how users use every means possible in the political battlefield on social media. Online Information Review (2022).
- [82] Leo G Stewart, Ahmer Arif, and Kate Starbird. 2018. Examining trolls and polarization with a retweet network. In Proc. ACM WSDM, workshop on Misinformation and Misbehavior Mining on the Web.
- [83] Ana Stojanov. 2015. Reducing conspiracy theory beliefs. Psihologija 48 (2015), 251-266. Issue 3.
- [84] Victor Suarez-Lledo and Javier Alvarez-Galvez. 2021. Prevalence of health misinformation on social media: systematic review. Journal of medical Internet research 23, 1 (2021), e17187.
- [85] Yanqing Sun, Stella C. Chia, Fangcao Lu, and Jeffry Oktavianus. 2020. The Battle is On: Factors that Motivate People to Combat Anti-Vaccine Misinformation. Health Communication (10 2020), 1–10.
- [86] Yanqing Sun, Jeffry Oktavianus, Sai Wang, and Fangcao Lu. 2021. The Role of Influence of Presumed Influence and Anticipated Guilt in Evoking Social Correction of COVID-19 Misinformation. *Health Communication* (2 2021), 1–10.
- [87] Yuko Tanaka and Rumi Hirayama. 2019. Exposure to Countering Messages Online: Alleviating or Strengthening False Belief? Cyberpsychology, Behavior, and Social Networking 22 (11 2019), 742–746. Issue 11.
- [88] Tsukasa Tanihara, Shinichi Yamaguchi, Tomoaki Watanabe, and Hidetaka Oshima. 2022. Effects of corrections on COVID-19-related misinformation: cross-media empirical analyses in Japan. International Journal of Web Based Communities 18, 1 (2022), 41–63.
- [89] Li Qian Tay, Mark J Hurlstone, Tim Kurz, and Ullrich KH Ecker. 2022. A comparison of prebunking and debunking interventions for implied versus explicit misinformation. British Journal of Psychology 113, 3 (2022), 591–607.
- [90] Franklin Tchakounté, Ahmadou Faissal, Marcellin Atemkeng, and Achille Ntyam. 2020. A Reliable Weighting Scheme for the Aggregation of Crowd Intelligence to Detect Fake News. Information 11 (6 2020), 319. Issue 6.

- [91] Michail Vafeiadis, Denise S. Bortree, Christen Buckley, Pratiti Diddi, and Anli Xiao. 2019. Refuting fake news on social media: nonprofits, crisis response strategies and issue involvement. Journal of Product & Brand Management 29 (5 2019), 209–222. Issue 2.
- [92] Toni G. L. A. van der Meer and Yan Jin. 2020. Seeking Formula for Misinformation Treatment in Public Health Crises: The Effects of Corrective Information Type and Source. Health Communication 35 (4 2020), 560–575. Issue 5.
- [93] Jeyasushma Veeriah. 2021. YOUNG ADULTS'ABILITY TO DETECT FAKE NEWS AND THEIR NEW MEDIA LITERACY LEVEL IN THE WAKE OF THE COVID-19 PANDEMIC. Journal of Content, Community and Communication 13 (2021), 372–383. Issue 7.
- [94] Gaurav Verma, Ankur Bhardwaj, Talayeh Aledavood, Munmun De Choudhury, and Srijan Kumar. 2022. Examining the impact of sharing COVID-19 misinformation online on mental health. Scientific Reports 12, 1 (2022), 1–9.
- [95] Santosh Vijaykumar, Daniel T Rogerson, Yan Jin, and Mariella Silva de Oliveira Costa. 2022. Dynamics of social corrections to peers sharing COVID-19 misinformation on WhatsApp in Brazil. *Journal of the American Medical Informatics Association* 29, 1 (2022), 33–42.
- [96] Nguyen Vo and Kyumin Lee. 2019. Learning from fact-checkers: Analysis and generation of fact-checking language. Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval, 335–344.
- [97] Soroush Vosoughi, Deb Roy, and Sinan Aral. 2018. The spread of true and false news online. science 359, 6380 (2018), 1146-1151.
- [98] Emily K. Vraga, Leticia Bode, and Melissa Tully. 2021. The Effects of a News Literacy Video and Real-Time Corrections to Video Misinformation Related to Sunscreen and Skin Cancer. Health Communication (4 2021), 1–9.
- [99] Mason Walker and Katerina Eva Matsa. 2021. News consumption across social media in 2021. (2021).
- [100] Bairong Wang and Jun Zhuang. 2018. Rumor response, debunking response, and decision makings of misinformed Twitter users during disasters. Natural Hazards 93 (9 2018), 1145–1162. Issue 3.
- [101] Xin Wang, Fan Chao, Ning Ma, and Guang Yu. 2022. Exploring the Effect of Spreading Fake News Debunking Based on Social Relationship Networks. Frontiers in Physics (2022), 180.
- [102] Xin Wang, Fan Chao, and Guang Yu. 2021. Evaluating Rumor Debunking Effectiveness During the COVID-19 Pandemic Crisis: Utilizing User Stance in Comments on Sina Weibo. Frontiers in public health (2021), 1925.
- [103] Xin Wang, Fan Chao, Guang Yu, and Kaihang Zhang. 2022. Factors influencing fake news rebuttal acceptance during the COVID-19 pandemic and the moderating effect of cognitive ability. Computers in human behavior 130 (2022), 107174.
- [104] Yuxi Wang, Martin McKee, Aleksandra Torbica, and David Stuckler. 2019. Systematic literature review on the spread of health-related misinformation on social media. Social science & medicine 240 (2019), 112552.
- [105] Derek Weber, Mehwish Nasim, Lucia Falzon, and Lewis Mitchell. 2020. #ArsonEmergency and Australia's "Black Summer": Polarisation and Misinformation on Social Media. 159–173 pages.
- [106] Jiechen Xu, Lei Han, Shaoyang Fan, Shazia Sadiq, and Gianluca Demartini. 2022. Does Evidence from Peers Help Crowd Workers in Assessing Truthfulness?. In Companion Proceedings of the Web Conference 2022. 302–306.
- [107] Haoning Xue, Xuanjun Gong, and Hannah Stevens. 2022. COVID-19 vaccine fact-checking posts on Facebook: observational study. Journal of medical Internet research 24, 6 (2022), e38423.
- [108] Fan Yang and Holly Overton. 2022. What If Unmotivated Is More Dangerous? The Motivation-Contingent Effectiveness of Misinformation Correction on Social Media. International Journal of Communication 16 (2022), 27.
- [109] Wenting Yu, Fei Shen, and Chen Min. 2022. Correcting science misinformation in an authoritarian country: An experiment from China. Telematics and Informatics 66 (2022), 101749.
- [110] Jing Zeng, Jean Burgess, and Axel Bruns. 2019. Is citizen journalism better than professional journalism for fact-checking rumours in China? How Weibo users verified information following the 2015 Tianjin blasts. Global Media and China 4 (3 2019), 13–35. Issue 1.
- [111] Yuqi Zhang, Bin Guo, Yasan Ding, Jiaqi Liu, Chen Qiu, Sicong Liu, and Zhiwen Yu. 2022. Investigation of the determinants for misinformation correction effectiveness on social media during COVID-19 pandemic. *Information Processing & Management* 59, 3 (2022), 102935.
- [112] Liming Zhao, Jianli Yin, and Yao Song. 2016. An exploration of rumor combating behavior on social media in the context of social crises. *Computers in Human Behavior* 58 (5 2016), 25–36.
- [113] Arkaitz Zubiaga, Elena Kochkina, Maria Liakata, Rob Procter, and Michal Lukasik. 2016. Stance classification in rumours as a sequential task exploiting the tree structure of social media conversations. arXiv preprint arXiv:1609.09028 (2016).