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Exploring the Effect of Spreading Fake News Debunking Based on Social Relationship Networks

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Fake news spreads rapidly on social networks; the aim of this study is to compare the characteristics of the social relationship networks (SRNs) of refuters and non-refuters to provide a scientific basis for developing effective strategies for debunking fake news. First, based on six types of fake news published on Sina Weibo (a Chinese microblogging website) during 2015–2019 in China, a deep learning method was used to build text classifiers for identifying debunked posts (DPs) and non-debunked posts (NDPs). Refuters and non-refuters were filtered out, and their follower–followee relationships on social media were obtained. Second, the differences between DPs and NDPs were compared in terms of the volume and growth rate of the posts across various types of fake news. The SRNs of refuters and non-refuters and the *k*-core decompositions of these SRNs were constructed, and the differences in the growth rates between DPs and NDPs were explored. Business-related fake news was revealed to be debunked better; society-related fake news, the most widely spread in China, was debunked poorly; and science- and politics-related fake news was debunked the worst. Additionally, more celebrity accounts, larger node sizes with follower-followee relationships in the SRNs, and more weakly connected components were found to lead to a faster growth rate in the dissemination of posts, regardless of whether the posts were DPs or NDPs. This study can help practitioners develop more effective strategies for debunking fake news on social media in China.

Keywords: fake news, stance detection, deep learning, debunking, refuter, social relationship network

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INTRODUCTION

Since the 2016 U.S. presidential election, "fake news" has become a common term in the mainstream vernacular [1, 2]. Similar to Western countries, fake news is also prevalent in China [3], and it largely involves online rumors (*yao yan* in Chinese [4]). Furthermore, with the rapid development of social networking services (SNSs), each user in a social network has become both a spreader and receiver of information, and millions of people present, comment on, or share various topics on social media every day [5]. In addition, the emergence of social media as an information dissemination channel has reduced the gap between content producers and consumers and profoundly changed the way users obtain information, debate, and shape their attitudes [6, 7]. Although authoritative organizations such as the government and news media have made considerable efforts to debunk fake news, social media enables individuals to rapidly distribute fake news through social networks owing to its abundance of users and complex network structure, causing considerable panic in society [8, 9].

Effective debunking can be considered as a competition between debunked and non-debunked information. Thus, if we need to reduce and combat the proliferation of fake news on social media, we must improve the identification of the spread of the differences between debunked and non-debunked information on social media, make debunked information an effective hedge against non-debunked information, and understand the structure and functions of these technologically advanced social networks [10].

A better understanding of debunking strategies associated with different types of fake news can help address fake news more specifically on social media. As most researchers have concentrated on politically sensitive or field-specific fake news on social media, it has been difficult to derive common rules applicable to countering all types of fake news generated within a certain field [11]. Although in previous studies, the differences between the spread of facts and that of rumors on Twitter across various topics [12] or between the typical features of rumor and anti-rumor accounts on Sina Weibo [9] have been comprehensively evaluated, the differences between different types of debunked and non-debunked fake news based on real data on Chinese social media have been thoroughly assessed in only a few studies.

Social media (e.g., Sina Weibo) are information dissemination platforms based on social relationships (follower-followee relationships), wherein information dissemination is closely related to people's social relationships [13], especially in networks that are large, complex, heterogeneous, and scalable [14]. Thus, people's social relationships and information dissemination networks are interrelated and mutually reinforcing. The breadth and depth of people's social relationship networks (SRNs) determine the breadth and depth of the information they obtain and how far the dissemination of this information can spread. Although the methods used for the study of fake news, such as fake news debunking detection (e.g., using features extracted from news articles and their social contexts, such as textual features and users' profiles [15]) and diffusion network structure analysis (e.g., reposting or commenting networks [16]), have been identified, the ways in which users' social relationships on social networks influence the spread of debunking messages have not been widely investigated. Additionally, these problems are important to address because, if a debunking methodology for fake news is not shared quickly and widely on social networks, people will fail to combat fake news in a timely and effective manner. Consequently, false information will continue to misguide public opinion on social media [17].

To meet the aforementioned objectives, first, we used a dataset containing 49,278 posts from 176 fake news events published on Sina Weibo from July 2015 to September 2019 and divided the fake news into six topics. Second, we developed a text classifier using deep learning by applying a long short-term memory (LSTM) algorithm to identify debunked posts (DPs) and non-debunked posts (NDPs), filtered the corresponding refuters and non-refuters, and obtained 74,987 follower-followee relationships between these refuters and non-refuters. Third, we analyzed the differences in the volume and growth rates between the DPs and NDPs for each type of fake news by comparing them in terms of the number and cumulative probability distribution of the posts. Fourth, for each type of fake news, we constructed SRNs involving refuters and non-refuters and the k-core decompositions of these SRNs; then, we investigated the proportion of each account type, the network size of the k-core decompositions of the SRNs, and the number of weakly connected components to explore the differences in the growth rates between DPs and NDPs. Finally, we analyzed the reasons for these differences across different types of fake news. Based on these results, we propose personalized and real-time governance strategies to serve as a guide for promoting healthier behavior among social media users and minimize the spread of fake news.

The contributions of this study are significant both in theory and practice. First, unlike previous research that focused on the sharing of fake news [6, 18], in this study, by using deep learning method and social network analysis method, we focus on the comparison of differences between the debunking and non-debunking of fake news across various topics and systematically construct, compare, and analyze the SRNs of refuters or non-refuters to provide strategies for combating various categories of fake news on Chinese social media at the macro level. Thus, we shift the scholarly focus from the dominant area of fake news information sharing to the emerging area of employing users and the social relationships among them to combat various types of fake news on Chinese social media platforms. Second, on a practical level, the "fake news" literature in China is expanded by focusing on various types of day-to-day online rumors on social media available from a large volume of fake news datasets. This study provides insight to practitioners such as social media managers, government staff, news authorities, and media staff on ways to debunk different types of fake news using targeted and personalized governance strategies.

The remainder of this paper is structured as follows. *Related Work* introduces work related to this study. *Materials and Methods* describes the data and methods. *Results* details the results of the experiments. *Discussion* presents a discussion on this study, the limitations of this study, and a scope for future work. *Conclusion* provides the conclusions of the study.

RELATED WORK

Before introducing the study problem, we provide brief remarks on the terminology used. Researchers have provided different interpretations of the definitions and connotations of fake news, misinformation, and rumors; these terms are often used interchangeably in academic research [19]. First, we disregarded the politicized nature that the term "fake news" has indicated, especially since the 2016 U.S. presidential elections. Second, we adopted a broader definition of news on social media: it includes any information (e.g., text, emoticons, and links) posted on social media [12]. Third, we did not consider the intentions behind those who posted the online information [2] and the differences between automated social robots and humans [12]. For these reasons and owing to its useful scientific

TABLE 1 | Summary of some previous work related to debunking fake news.

Category	References
Fact Checking	CredFinder [21]; Hoaxy [22]; Snopes [24]; PolitiFact, FactCheck, TruthOrFiction, and Sina Community Management Centre [2, 8, 17, 23]
Source Detection	Source localization algorithm for probabilistic weighted graph [34]; path-based approach [31]; variants of epidemic models [32]; and batch and interactive query approaches [33]
Propagation Dynamics	Soft computing models, such as the heat energy model [36]
	Epidemiological models and their variants, such as the SI model, SIR model, SIS model, SIRS model, SEIS model [37], and G-SCNDR model [38]
	Mathematical models, such as the linear threshold model [41], independent cascade model [40], and stochastic model [39]
Fake News Detection	Datasets and experimental settings, including the details of the dataset, size, amount of fake or real news, and information used for detection [12, 43–46]
	Handcrafted feature extraction, including text (e.g., number of words and/or sentences [48], first/second/third person pronouns [47]), sentiment analysis (positive, negative, any other [12]), images (e.g., number of faces [47], image statistical features [49]), users (e.g., name, location, gender [50]), messages [e.g., messages with URL [50] or hashtags (#) [51]], propagation (e.g., degree of root in a propagation tree, depth of the propagation tree [52]), structural [48], temporal [53], and linguistic specific features [54]
	Studying network structures, including getting credibility assessment methods [55, 56] and modeling network structures and the user connectivity of online social networks (e.g., generative graph models [57])
	Machine learning and deep learning classifiers, including machine learning techniques [e.g., SVM, decision tree, k-NN algorithm, random forest (RF)] and deep learning techniques (e.g., RNN, LSTM) [59–64, 66, 67]
	Other methods, such as cognitive psychology methods [65]

meaning and construction, we retained the term "fake news," which is used by most researchers, to represent our research objective [1, 8]; this term refers to false news or false rumors stemming from authorities' (e.g., government agencies, state media, and other authoritative organizations) statements that were determined to be false.

Social media platforms employ different approaches to combat online fake news. The first key strategy is to undermine economic incentives and shift focus to developing technical solutions to help users make more informed decisions [20], for example, by showing warning messages and relying on fact-checking units [2, 8, 17, 21–24]. In this context, Hoaxy is a platform used for the collection, detection, analysis, and fact-checking of fraudulent online content from various viewpoints [22]. It was tested by collecting approximately 1,442,295 tweets and articles from 249,659 different users [16]. Content from news websites and social media was fed into a database that was updated on a regular basis, and it was analyzed to extract different hidden patterns [22]. Pennycook et al. selected fake news headlines from Snopes.com, a third-party website that fact-checks news stories, to investigate whether warning tags would effectively reduce belief in fake news by a prominent intervention that involved attaching warnings to the headlines of news stories that have been disputed by third-party fact-checkers [24]. Although researchers and online fact-checking organizations are continuously improving their fact-checking measures against the spread of fake news, most fact-checking processes depend on human labor, which requires considerable time and money [25, 26]. Despite recent advancements in automatic detection, identification models for fact checking lack the required adaptive and systematic applications [2]. **Table 1** lists popular fact-checking analysis tools that are used to check the authenticity of online content.

Social network analysis has become a widely accepted tool [27]. Thus, the second key strategy is broadcasting denials to the public to prevent the exposure of individuals to fake news on social media [8], which can reduce the possibility of fake news spreading [28]. Fake news often spreads over social media through interpersonal communication [23], and personal involvement remains a salient construct of the spread of fake news on social media [29]. Thus, the key approach to combat the spread of fake news is to use the power of social relationships on social networks to spread messages from one individual to another [30]. Some researchers preferred to examine interventions on social networks that might be effective in debunking fake news by using source detection, i.e., finding out the person or location from whom or where the false information in the social network or web started spreading [16, 31–35] (see **Table 1**). For example, Shelke and Attar provided a state-of-the-art survey of different source detection methodologies along with different available datasets and experimental setups in case of existing single and multiple misinformation sources [35]. Whereas other researchers preferred to investigate the propagation dynamics of fake news [16]. As shown in **Table 1**, the prominent methods of fake news diffusion models available in the literature can be classified into three major categories: soft computing [36], epidemiological [37, 38], and mathematical approaches [39–41]. It is hard to execute these approaches because most of these studies are based on complex mathematical, physical, and epidemiological models; furthermore, in the real world, users may go beyond just controlling the simulation settings in the diffusion models [17].

The third key strategy is fake news detection. Different artificial intelligence algorithms along with cognitive psychology and mathematical models are used to identify false content [16]. As the assessment of the veracity of a news story is complex from an engineering point of view, the research community is approaching this task from different perspectives; **Table 1** presents some prominent research on datasets, experimental settings, training, validation, and testing

methods used in various machine learning and deep learning technologies, and other methods to address the issue [16, 42] (see **Table 1**).

As presented in **Table 1**, the first research aspect is the study of datasets and experimental settings. Different formats of datasets are used for content and behavioral analyses such as text tweets, images, headlines, news articles, URLs, users' comments, suggestions, and discussions on particular events [16]. Most researchers used Twitter, Sina Weibo, and Facebook's Application Programming Interface (API) for collecting and analyzing rumors and fake news as data sources [12, 43, 44], whereas other researchers preferred using a data repository such as FakeNewsNet that contains two comprehensive datasets PolitiFact and GossipCop to facilitate research in the field of fake news analysis [45]. These datasets collect multi-dimensional information from news content and social contexts and spatiotemporal data from diverse news domains [16]. In addition, some researchers compared the details of some of the widely used datasets and experimental setups in detail [46].

The second research aspect is the study of handcrafted feature extraction. Machine and deep learning are prominent techniques for designing models for detecting false information. The effectiveness of these algorithms mainly depends on pattern analysis and feature extraction of text [12, 47, 48], images [47, 49], users [50] messages [50, 51], propagation [52], structural [48], temporal [53], and linguistic specific features [16, 54] (see **Table 1**).

The third research aspect is the study of network structures. Network structures are innovative methods of assessing the credibility of a target article [55]. For example, Ishida and Kuraya proposed a bottom-up approach with relative, mutual, and dynamic credibility evaluation using a dynamic relational network (or mutual evaluation model) of related news articles, wherin each node can evaluate and in turn be evaluated by other nodes for credibility based on the consistency of the content of the node [56]. In addition, to model network structures and the user connectivity of online social networks, scalable synthetic graph generators were used by researchers. These generators provided a wide variety of generative graph models that could be used by researchers to generate graphs based on the extraction of different features such as propagation, temporal, connectivity, follower-followee relationship [16]. For example, Edunov et al. proposed Darwini, a graph generator that captures several core characteristics of real graphs and can be used efficiently to study the propagation and detection of false content by generating different social connections in the form of a graph [57]. To accomplish this, Darwini produces local clustering coefficients, degree distributions, node page ranks, eigenvalues, and many other matrices [57].

The fourth research aspect is the study of machine learning and deep learning classifiers. Some scholars have investigated real-time data in social media sites using stance detection methods to identify people who are supportive, neutral, or opposed to fake news [58]. These methods are widely based on the computation of machine or deep learning algorithms to achieve open or target-specific classification [59–61]. For example, Pérez-Rosas et al. focused on the linguistic differences between fake news and legitimate news content by using machine learning techniques, including a linear support vector machine (SVM) classifier, and obtained 78% accuracy in detecting fake news on two novel datasets [62]. The major disadvantage of machine-learning-based models is that they are dependent on hand-crafted features that require exhaustive, meticulous, detailed, and biased human efforts; thus, recent technologies are shifting the trend towards deep learning-based models [16]. For example, Zarrella and Marsh applied a recurrent neural network (RNN) initialized with features learned *via* distant supervision to tackle the SemEval-2016 task 6 (Detecting Stance in Tweets, Subtask A: Supervised Frameworks) [63]. In parallel, they trained embeddings of words and phrases with the word2vec Skip-Gram method. This effort achieved the top score among 19 systems with an F1 score of 67.8%, and one of 71.1% in a non-official test. Poddar et al. developed a novel neural architecture for detecting the veracity of a rumor using the stances of people engaging in a conversation about it on Twitter [64]. Taking into consideration the conversation tree structure, the proposed CT-Stance model (stance predictor model) achieved the best performance with an accuracy of 79.86% when considering all three realistically available signals (target a tweet, conversation sequence, time). In addition, there are other fake news detection methods, such as the use of cognitive psychology to analyze human perceptions. For example, Kumar and Geethakumari explored the use of cognitive psychology concepts to evaluate the spread of misinformation, disinformation, and propaganda in online social networks by examining four main ingredients: the coherency of the message, credibility of the source, consistency of the message, and general acceptability of the message; they used the collaborative filtering property of social networks to detect any existing misinformation, disinformation, and propaganda [65].

Based on the analysis of the aforementioned related work, some previous studies on fake news debunking are summarized in **Table 1**. First, the differences between different types of debunked and non-debunked fake news based on real data on Chinese social media have not been comprehensively assessed; second, the ways in which users' social relationships on social networks influence the spread of debunking messages have also not been fully investigated. Unlike previous studies, we used a deep learning method to build text classifiers for identifying debunked posts (DPs) and non-debunked posts (NDPs), and filtered out refuters and non-refuters. Then based on social analysis method, we focused on the empirical analysis of real data on Chinese social media platforms by comparing the characteristics of the SRNs of refuters and non-refuters, and we tried to discover useful strategies for debunking different categories of fake news effectively.

MATERIALS AND METHODS

Study Context and Data Collection

Sina Weibo, often referred to as "Chinese Twitter," is one of the most influential social network platforms in China [68]. Twitter is a widely used microblogging platform worldwide, and its content

is mainly written in English, while Sina Weibo is the most famous microblogging platform in China, where all posts are written in Chinese [69]. Social media are known as interactive computer-mediated technologies that allow people to create, share or exchange information [69]. The increasing popularity of social media websites and Web 2.0 has led to an exponential growth of user-generated content, especially text content on the Internet [69], which generates a large amount of unstructured text data and provides data support for our research. Thus, to avoid selection bias in the data, our data were collected from Zhiwei Data Sharing Platform's (hereinafter referred to as Zhiwei Data) database that contains fake news of public events posted on Sina Weibo from July 2015 to September 2019, among which all the fake news events have been verified as "false." We then obtained 176 widely spread fake news events, for a total of 49,278 posts. We also cooperated with Zhiwei Data to obtain user profiles through the business API of Sina Weibo, including the demographic characteristics of the users, such as their names, genders, types of accounts, locations, the number of their posts, followees, and followers, the source of their posts, and their posting times.

As publicly available data were used in this study, we only referred to the summarized results and did not derive any sensitive data. Information on the individuals studied in this research has not been published elsewhere.

Methodology

Identification of Debunked Fake News Posts

Fake news contains partly true, false, and mixed information; thus, researchers need to know what kind of opinions are expressed by people communicating on social media; this can be determined through stance detection [58]. A stance is a person's opinion on or attitude toward some target entity, idea, or event determined from a posting, e.g., "in favor of," "neutral," "against," [70], "support," "deny," "comment," or "query" [71]. According to the content of 176 fake news events, we considered both subjective expressions and their corresponding targets, which might not be explicitly mentioned, and labeled each stance with respect to a specific target of each event; each stance was divided into two relative standpoints, "against" and "other," corresponding to DPs from refuters and NDPs from non-refuters, respectively. Additionally, a text classifier was developed to detect DPs, which indicated that people who made these posts were against fake news. Although we acknowledge that binary labeling has certain limitations, for our current research, we highlighted the main research objectives as well as the overwhelming advantages of this straightforward and simple classification when compared to its weaknesses [72].

Stance detection is an area with closely related subjects [58]. Thus, it is modeled as a supervised learning process to achieve better results when a training dataset is required. Therefore, to obtain a fully available dataset, we asked three members of our team to label posts using an "against" or "other" stance. Two members with a detailed understanding of fake news labeled 10,000 posts, which were randomly selected from 49,278 posts. Furthermore, we tackled this labeling analysis based on the conversations stemming from direct and nested replies to the posts originating from fake news [71]. Next, these two members discussed all the annotation results and reannotated the posts to agree on the differences. Finally, a third member randomly selected 1,000 posts from 10,000 posts for an annotation to calculate the intercoder reliability. In addition, Cohen's kappa is popular descriptive statistics for summarizing the cross-classification of two nominal variables with $n \in N_{\geq 2}$ identical categories [73, 74]. An $n \times n$ table can for example, be obtained by cross-classifying the ratings of two observers that each have classified a group of objects into n categories. In this case, the $n \times n$ table can be referred to as an agreement table, since it reflects how the ratings of the two observers agree and disagree [73]. Based on the above analysis, to calculate the inter-annotator agreement, we assessed the validity of the annotation scheme using Cohen's kappa. The Cohen's kappa (κ) value for the members was 0.889 ($p < 0.001$), indicating a good agreement between them [75]. Finally, 5,613 DPs were labeled from the 10,000 posts.

According to the external references in a stop word dictionary, we used Python's (Version 3.6.2) regular expressions to clean the sample data (including the compile and sub methods in Python's RE package), including removing the relevant stop words (based on the list of stop words produced by the Harbin Institute of Technology), URLs, and punctuation and correcting any misspelt words. Then, we created our user dictionary, which includes some terms related to the 176 fake news events, and we used the Jieba Chinese text segmentation module in Python, one of the most widely used word segmentation tools for the Chinese, to segment the sample data. We then used word2vec from Google for word embedding [76]. The vector representations of words learned by word2vec can extract the deep semantic relationships between words, contributing more to text classification [77].

A long short-term memory (LSTM [78]) network was developed on the basis of recurrent neural networks (RNNs), which are capable of processing serialized information through their recurrent structures, to solve problems related to gradient vanishing or exploding [79]. LSTM does show a remarkable ability in processing natural language. Particularly, on Chinese social media posts where the words have complex context-dependent relationships, LSTM models perform well in applications with text classification tasks [79, 80]. Therefore, a deep neural network with an LSTM algorithm was employed to build the text classifier. In the LSTM model training process, the hyperparameter is a parameter that sets the value before the model is trained. Generally, the hyperparameters need to be optimized, and a set of optimal hyperparameters is selected for the model to improve the quality of the learning [81]. To prevent the overfitting problem of the model in the training process, we selected some appropriate combinations of parameters to train the model, and the hyperparameter configuration of the model was as follows: batch size = 512; maximum length of the sentence = 70; dropout = 0.5; activation = sigmoid; loss function = binary cross-entropy.

Then, we tested the vector dimensions of 50, 100, 150, . . . , 450, and 500 to obtain the best word vector dimension. We chose accuracy and F1 score as metrics to measure the performance of

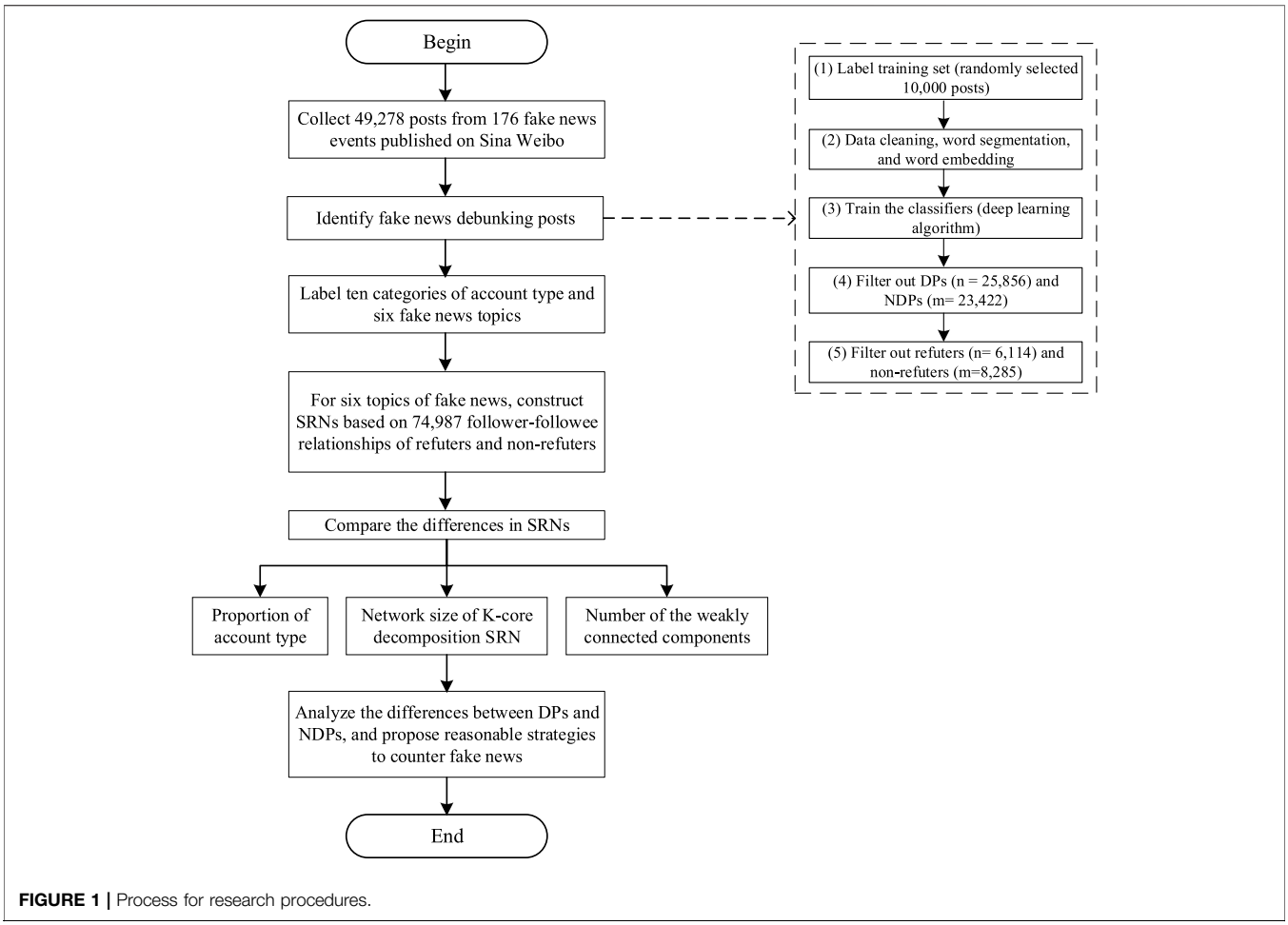

FIGURE 1 | Process for research procedures.

TABLE 2 | Results of the classification.

Dimensions of vectors	Accuracy (%)	F1 score (%)
50	86.37	88.63
100	89.58	91.02
150	89.68	90.78
200	90.58	91.44
250	90.88	91.94
300	90.38	91.64
350	90.98	92.05
400	90.38	91.13
450	90.48	91.66
500	90.78	91.70

the classifiers [82]. A 10-fold cross-validation technique was also adopted to train our classifier and evaluate the performance of our classification algorithm. The experimental results of the classification are presented in **Table 2**. Compared with other dimensions, the experimental results had a relatively high accuracy of 90.98% and an F1 score of 92.05% with a word vector dimension of 350. Thus, we used a word vector dimension of 350 to build our classification. Finally, we obtained 25,856 DPs from 6,114 refuters and 23,422 NDPs from 8,285 non-refuters using our classifier. A flowchart for identifying debunked fake news posts is shown in **Figure 1** [see procedures (1–5) in **Figure 1**].

Qualitative Classification of Account Types and Fake News Topics

First, to analyze and examine how various accounts (refuters and non-refuters) were involved in DPs and NDPs, we referred to account classification standards based on the Sina Weibo certification on their homepages, which includes ten types of accounts: ordinary, media, government, celebrity, Weibo's got talent, enterprise, campus, organization, website, and Weibo girl.

Second, we referenced the fake news classification standards of Twitter [12] and previous studies regarding the rumor classification standards of Sina Weibo in China [83]. We divided the fake news into six categories using the Zhiwei Data's classification criteria: society, health, business, science and technology (hereinafter referred to as science), disaster, and politics and finance (hereinafter referred to as politics) (**Table 3**). We also asked three annotators from Zhiwei Data to label 176 events according to these six categories. Additionally, the Cohen's kappa (κ) value for the annotators was 0.961 ($p < 0.001$), indicating that the classification results were robust.

TABLE 3 | Examples for six categories of fake news (Translated into English from Chinese).

Category	Example
Society	• Netizens reporting that children in Bijie's orphanage were sexually abused was a rumor • A courier crying in the rain because of a quarrel with his girlfriend was a rumor
Health	• Ham and bacon being carcinogenic when taken with arsenic was a rumor • Meat pine in meat muffin being made of cotton was a rumor
Business	• Was the woman involved in the case of Qiangdong Liu taken into custody? The U.S. police responded that it was not true • Huawei dispelled the rumor that cooperation with the Longping Yuan company to cultivate rice was a rumor
Science and Technology	• Officials dispelled the rumor that the third generation ID card increased the positioning function was a rumor • The possibility of the electronic marriage certificate replacing the paper certificate was a rumor
Disaster	• The Gansu Zhangye 5.0 magnitude earthquake causing the road to vibrate in a "wave-like" manner was a rumor • Heavy rainstorm in the Sichuan Province due to the movement of a "water beast" was a rumor
Politics and Finance	• The China–U.S. trade war ceasefire was a rumor • Stopping the circulation of one-yuan banknotes in the near future was a rumor

Notes: Data Source: Zhiwei Data Sharing Platform (http://university.zhiweidata.com/).

For each type of fake news, we used the number of posts to indicate the spreading volumes of the DPs and NDPs. We also sorted each event in ascending order according to the time of the post and calculated the relative hours of any post relative to the first post in each news event. For the six types of fake news, we aggregated all their corresponding events. Here, the epoch t was set to 1 h because of data sparsity and the 24 h daily schedule. Therefore, for the six types of fake news, we used p_r to represent the cumulative probability of propagation at any hour t of the DPs or NDPs to indicate the growth rates of their spread, based on the method of Liu et al. [84], and we defined the following:

$$p_r = \frac{n_{(i,j)}(t)}{n_{(i,j)}(t \to \infty)}, \tag{1}$$

where $n_{(i,j)}(t)$ represents the cumulative total of the posts with the type j in the fake news of category i until time t, $t \to \infty$ denotes the time when the propagation of the fake news of category i ends, j represents two types of posts ($j = 0$, DPs; $j = 1$, NDPs), i represents six categories of fake news ($i = 1, 2, \ldots, 6$, which represents society, health, business, science, disaster, and politics, respectively).

Social Relationship Network Construction and Analysis

On Sina Weibo, users (followers) may choose to follow any other users (followees); thus, they can automatically receive all the posts published by their followees, such as on Twitter [85]. Here, an SRN with weak ties is formed; users can easily follow many people without talking to them directly. Thus, we filtered out all the follower-followee relationships (hereinafter referred to as following relationships) of 6,114 refuters and 8,285 non-refuters involved in spreading fake news. We also filtered the source nodes (followers) and target nodes (followees) in the following relationship of users involved in fake news propagation and finally obtained 74,987 following relationships.

A set of following relationships and the set of Sina Weibo users connected by these relationships formed an SRN [85]. Relationships between people can be captured as graphs where vertices represent entities and edges represent connections among them [86]. A k-core of a graph is a maximal connected subgraph in which every vertex is connected to at least k vertices in the subgraph [87]. The k-core decomposition of a graph maintains, for each vertex, the max-k value: the maximum k value for which a k-core containing the vertex exists [86]. At the same time, k-core decomposition is often used in large-scale network analysis [86]. For example, the k-core decomposition was recently applied to several real-world networks (the Internet, the WWW, etc.) and was turned out to be an important tool for visualization of complex networks and interpretation of cooperative processes in them [87, 88]. Thus, to explore the network structure of the participants' social relationships, for both refuters and non-refuters, we established SRNs under each topic and their k-core decompositions based on the following relationships between the users ($2 \times 2 \times 6 = 24$); the networks were directed and unweighted. In an SRN, each user is a node; if user i follows user j, then there is a directed edge from i to j, and isolated nodes denote users without a following relationship with anyone in the network. To better investigate the following relationships between refuters in DPs and those between non-refuters in NDPs, we divided all the users participating in the discussion into four categories for each type of fake news as follows: SRN of refuters (refuter–refuter SRN, R–R), k-core decomposition of SRN of refuters (refuter–refuter k-core decomposition of SRN, R_k–R_k), SRN of non-refuters (non-refuter–non-refuter SRN, NR–NR), and k-core decomposition of SRN of non-refuters (non-refuter–non-refuter k-core decomposition of SRN, NR_k–NR_k).

We computed the following set of basic network properties, which allowed us to encode each network according to a tuple of features: (1) the average degree ($< K >$), (2) the diameter (D), (3) the average clustering coefficient (CC), and (4) the average path length (L) [15, 89], where $< K >$ is characterized by the average of the degrees of the nodes in the SRN and measures the average influence of the nodes in the SRN; D is characterized by the maximum value of the shortest distance between any two nodes in the network and measures the maximum length of any

following relationship in the network; *CC* is characterized by the average of the clustering coefficients of the nodes in the network and measures the cohesive size of the network; and L is characterized by the average value of the shortest distance between the nodes in the network, which measures the average length of any following relationship in the network.

Note that our analysis is based on the fact that fake news propagation has already ended; we did not construct a reposting network. Some of the network indicators (1–4) in the aforementioned network analysis are only descriptions and portrayals of the basic properties of the network and cannot be used to explain the reasons for the differences in the propagation of DPs and NDPs. Therefore, to compare SRNs more effectively, we considered defining measurement indices based on the following three aspects. First, we considered that some accounts exhibited different characteristics in the spread of fake news [18] and that there might be some individual differences, that is, different types of nodes might play different roles in the spread. Second, in interpersonal communication, fake news tends to initially flow to neighbors, friends, and colleagues of the spreaders and then circulate in certain regions and groups; thus, we used the size of the nodes with social relationships to symbolize the magnitude of this spreading effect. Furthermore, if a shortcut existed between two local cliques, was more conducive to the spread of information, and the number of weakly connected components on social networks indicated the magnitude of this influence. Therefore, we defined the following three measure indices:

(1) Proportion of account types (*Ratio*)

To avoid differences in the sizes of the SRNs of different types of fake news, we considered the relative index of the proportion of account types participating in DPs and NDPs as follows:

$$Ratio = \frac{DP_{ik}}{NDP_{ik}}, \tag{2}$$

where DP_j and NDP_j represent the proportion of account type k in DPs and NDPs in the fake news of category i, where i = 1, 2, ..., 6 represents society, health, business, science, disaster, and politics, respectively ; k = 1, 2,..., 5 represents ordinary users, media, government, celebrity, and other types of accounts (including Weibo got talent, enterprise, campus, organization, website, and Weibo girl accounts) , respectively.

(2) Network size of the k-core decomposition of an SRN (*Size*)

To avoid the differences in the scales of the SRNs of different types of fake news, we considered analyzing the ratio of the number of nodes in the SRNs before and after k-core decomposition to measure the scale of the SRNs and determine the size of nodes with following relationships in the k-core decompositions of the SRNs; accordingly, we defined size as follows:

$$Size = \frac{K_Nodes_{ij}}{Nodes_{ij}}, \tag{3}$$

where $Nodes_{ij}$ and K_Nodes_{ij}, respectively, represent the number of nodes in the SRNs before and after their k-core decompositions for the fake news of category i, for refuters or non-refuters, where i = 1, 2, ..., 6 represents society, health, business, science, disaster, and politics; and j = 0, 1 represents refuters and non-refuters, respectively.

(3) Number of weakly connected components (*Nwcc*)

A weakly connected component of a directed graph is a maximal (sub)graph, where there exists a path $u \leftrightarrow v$ ignoring edge directions for each pair of *vertices* (u, v) [15].

Additionally, we used the open-source software Gephi 0.9.2 to visualize networks and calculate the network properties [90, 91]. In the network, nodes were colored according to ten types of accounts, and the sizes of the nodes corresponded to their total degree (including the in-degree and out-degree), that is, the number of followees and followers of this account, which is a measure of the influence of an account. The Fruchterman-Reingold layout algorithm was used to calculate the graph layout and draw a graph by force-directed placement [92].

Statistical Analyses

Pearson chi-square (χ^2) tests were performed to compare the differences in the distributions of DPs and NDPs across each fake news topic, as well as the differences in the account distributions of DPs and NDPs across each fake news topic [93]. Wilcoxon rank sum tests were used to measure the differences in the number of posts between DPs and NDPs across each fake news topic over time [94]. The Pearson chi-square (χ^2) test and Wilcoxon rank sum test were conducted by SPSS for Windows, version 25.0.0 (IBM Corporation).

Research Procedures

The process followed in this study is illustrated in **Figure 1**. First, we collected 49,278 posts of 176 fake news events on Sina Weibo from July 2015 to September 2019. Second, we used the LSTM algorithm to build a stance classifier, which divided posts into DPs and NDPs and filtered out refuters and non-refuters for further analysis. Third, we divided the account types into ten categories and fake news into six topics. Fourth, for each type of fake news, we obtained 74,987 following relationships of refuters and non-refuters and constructed SRNs and their k-core decomposition SRNs. Fifth, we analyzed the differences in the volume and spreading growth rates between DPs and NDPs for each type of fake news by comparing the posts in terms of number and cumulative probability distribution. For each type of fake news, we analyzed the differences in the spreading growth rates of DPs and NDPs, as well as the reasons for these differences by investigating the proportion of account types, the network sizes of the k-core decompositions of the SRNs, and the number of weakly connected components. Finally, we provide recommendations for combating fake news on social media.

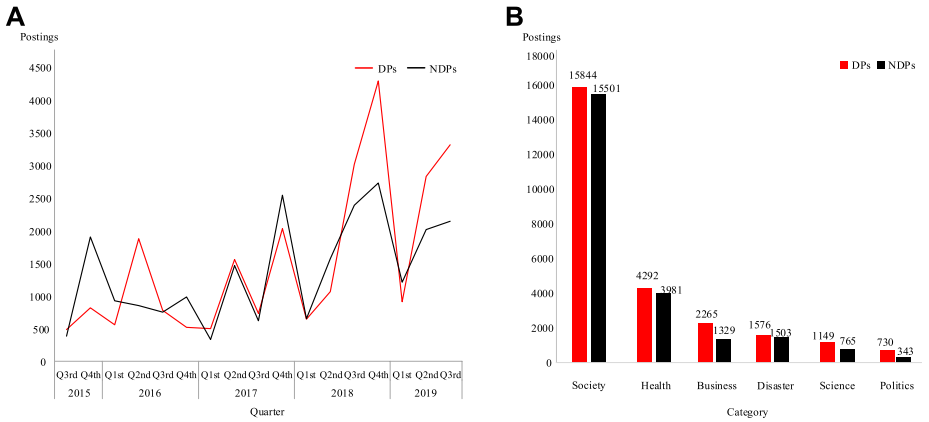

FIGURE 2 | Descriptive analysis of DPs and NDPs: **(A)** quarterly DPs and NDPs and **(B)** the number of DPs and NDPs under the six fake news topics. Notes: Science represents science and technology and Politics denotes politics and finance.

RESULTS

Development of Debunked and Non-Debunked Posts Over Time

Distribution of Debunked and Non-Debunked Posts

To achieve a better comparison between DPs and NDPs, we used graphs for clearer data representation. The quarterly numbers of all the DPs and NDPs diffused on Sina Weibo from July 2015 to September 2019 are shown in **Figure 2A**. Owing to the scarcity and imbalance of the dataset at certain periods and for better comparison with the research on Twitter [12], we used quarterly data for the representation in **Figure 2A**. Note that the spread of fake news has increased yearly, particularly in 2018 and 2019. Similarly, the spread of DPs has gradually but significantly increased, especially in the third and fourth quarters of 2018; furthermore, the number of DPs is much higher than that of the NDPs, and the gap between the DPs and NDPs is gradually increasing ($p < 0.001$).

The total number of DPs and NDPs for various types of fake news are shown in **Figure 2B**. The result of the Pearson chi-square test was $\chi^2(25) = 117110$ ($p < 0.001$), indicating that the result had a very high degree of statistical significance. **Figure 2B** demonstrates that society-related fake news was the largest category of fake news in Chinese social media platforms, with 15,844 DPs and 15,501 NDPs, followed by health with 4,292 DPs and 3,981 NDPs; business-related fake news had 2,265 DPs and 1,329 NDPs, which differed from the distribution on Twitter (corresponding to politics, urban legends, business, terrorism, and war, respectively [12]). Similarly, DPs and NDPs showed a different trend, with more DPs than NDPs. We analyzed the reason for this because our research data are a review of historical data collected over a long period and the total number of DPs mostly exceeded that of the NDPs. However, the observation that the total number of DPs circulated was greater than that of NDPs circulated was insufficient to prove that this was an effective fake news rebuttal act.

Spreading Growth Rates of Debunked and Non-Debunked Posts

For the spread of fake news, early debunking is important to minimize harmful effects. Therefore, we considered further examining the differences in the propagation growth rates of DPs and NDPs. Using **Eq. 1**, we calculated the p_r for each type of fake news and plotted the cumulative probability distribution for six fake news categories of DPs and NDPs (**Figure 3**). Owing to the imbalanced dataset, the number of posts varied and was greater during certain periods. The cumulative probability distribution in the six fake news categories of DPs and NDPs (**Figure 3**) indicates that the differences in the growth rates of the spread of DPs and NDPs for the same propagation time with the p_r reaching a larger value, represented faster growth in speed during the same propagation time. For instance, as depicted in **Figure 3D**, after 70 h are completed, the p_r of the NDPs is always higher than that of the DPs, indicating that the NDPs spread faster than the DPs. **Figure 3** also indicates the time required for DPs and NDPs to reach a certain proportion of the same total number of posts for the same value of p_r, e.g., for $p_r = 0.5$, half of the propagation of DPs or NDPs of the respective total number of posts, the shorter time represents the increase in the growth in speed.

Figure 3 shows that for all types of fake news, in the first 1/3 propagation stage, the NDPs and DPs spread rapidly; however, the details of the spread patterns are different. Except for business-related fake news (as shown in **Figure 3C**, the p_r for DPs is close to NDPs; a low degree of statistical significance, $p = 0.943$), NDPs spread faster than DPs for the other five types of fake news (as shown in **Figures 3B–F**, the p_r for the NDPs is higher than that for the DPs; high degree of statistical significances, $p \in [0.000, 0.036]$). For all types of fake news, in the first 1/3 propagation stage, the p_r of NDPs can reach 0.8 and more, which can spread to more than 80% of the total number of NDPs; however, not all the p_r of the DPs can reach 0.8, such as science- (**Figure 3D**) or politics-related (**Figure 3F**) fake news. Therefore, our results showed that the spreading patterns of DPs

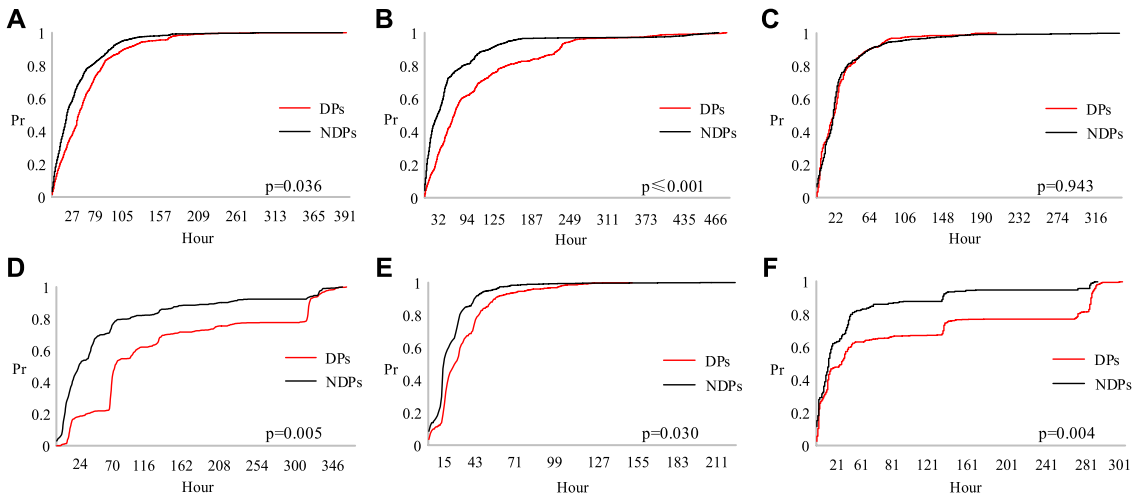

FIGURE 3 | Growth rate of debunked posts (DPs) and non-debunked posts (NDPs) in six categories of fake news over time: **(A)** Society, **(B)** Health, **(C)** Business, **(D)** Science, **(E)** Disaster, and **(F)** Politics. Notes: Science represents science and technology and Politics represents politics and finance.

and NDPs were different for various categories of fake news, indicating that the patterns may be related to the characteristics of the event. Specifically, for the six types of fake news, the debunking effect of the business-related fake news was better, where DPs can catch up with the speed of NDPs, whereas for other types of fake news, DPs did not spread as rapidly as NDPs. Fake news related to science (**Figure 3D**) and politics (**Figure 3F**) was debunked the worst, indicating that the response speed of the DPs was slower and the release of the debunking messages was not as timely compared with DPs in other categories.

Social Relationship Networks of Refuter–Refuter and Non-Refuter–Non-Refuter

Distribution of Account Types

To investigate the different roles played by the various types of accounts in the growth rate of DPs and NDPs, we first examined the proportion of accounts in all types of fake news; the results are shown in **Figure 4**. For DPs and NDPs, the Pearson chi-square tests indicated that the results had a very high degree of statistical significance in the account distribution under different types of fake news [**Figure 4A**: $\chi^2(20) = 937.751$, $p < 0.001$; **Figure 4B**: $\chi^2(20) = 349.891$, $p < 0.001$]. Media and celebrity account types accounted for most DPs in six types of fake news, and media accounts typically accounted for the largest proportion of DPs, with an average proportion of 57.64% in the six types of fake news events, followed by celebrity accounts, with an average proportion of 20.60%. In terms of account types in NDPs, however, media and celebrity accounts continued to be the most common, with an average proportion of 31.75% and 43.89%, respectively. Celebrity accounts accounted for the largest proportion of the four types of fake news events, namely politics (55.39%), science (49.15%), business (46.28%), and society (40.39%), whereas media accounts accounted for the largest proportion of health- (42.02%) and disaster-related fake news (38.46%).

Celebrity and media accounts played an important role in the spreading growth rates of DPs and NDPs. Therefore, combining the "80/20" distributions [95], we mainly focused on the role played by media and celebrity accounts in the propagation of DPs and NDPs, referring to **Eq. 2**. The results are shown in **Table 4**. We found that, for business-related fake news that achieved a better debunking effect on the spread of DPs, the relative proportion of the celebrity accounts in DPs to those in NDPs was the highest ($Ratio2 = 0.708$), whereas the relative proportion of media accounts in DPs to those in NDPs was the lowest ($Ratio1 = 1.495$). In contrast, for two types of fake news that had the worst debunking effects in the spread of DPs, namely, science- and politics-related fake news, the relative proportion of the celebrity accounts in DPs to those in NDPs was the lowest, at 0.292 and 0.361, respectively, whereas the relative proportion of the media accounts in DPs to those in NDPs was the highest, at 2.486 and 2.600, respectively.

Comparison of Differences in Networks of Refuters and Non-Refuters

To analyze the factors affecting the growth rate of DPs and NDPs for the six types of fake news, we constructed SRNs of refuters and non-refuters and the corresponding k-core decompositions of these SRNs and attempted to discover the factors affecting the growth rate of DPs and NDPs in terms of their network characteristics. Therefore, we constructed SRNs of refuters and non-refuters for each type of fake news and portrayed the SRNs using four basic network properties (**Figure 5**). We found that, in SRNs of refuters and non-refuters for each type of fake news event, the fake news categories with a better fake news debunking effect (business) and those with worse fake news debunking effects (society, health, disaster, politics, and science) did not

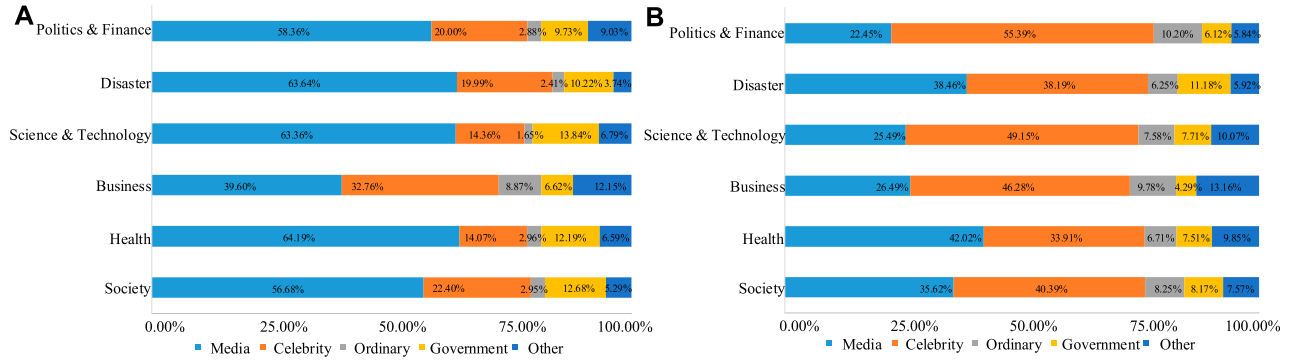

FIGURE 4 | Proportion of account types in **(A)** debunked posts (DPs) and **(B)** non-debunked posts (NDPs) under six types of fake news. Notes: Other types of accounts include Weibo got talent, enterprise, campus, organization, website, and Weibo girl accounts.

TABLE 4 | Relative proportion of account types in DPs and those in NDPs under six types of fake news.

Category	Ratio 1	Ratio 2
Society	1.591	0.555
Health	1.527	0.415
Business	1.495	0.708
Science and Technology	2.486	0.292
Disaster	1.655	0.523
Politics and Finance	2.600	0.361

Notes: Ratio1 denotes the relative proportion of media accounts in DPs to those in NDPs; Ratio2 denotes the relative proportion of celebrity accounts in DPs to those in NDPs.

show significant differences in the properties of $< K >$, D, CC, and L.

As shown in **Figure 5**, the fake news types with better debunking effects (business) and those with worse debunking effects (society, health, disaster, politics, and science) do not show significant differences in the properties of $< K >$, D, CC, and L. Therefore, to further analyze the influence of the following relationships between nodes (refuters or non-refuters) on the growth rate of DPs and NDPs, we performed k-core decomposition ($k = 1$) on the SRNs to remove the isolated nodes ($degree\,of\,nodes = 0$) without any following relationship and obtain the k-core decompositions of SRNs composed of nodes with following relationships. Furthermore, for different types of fake news, we examined the differences between the network sizes of the k-core decompositions of the SRNs and the number of weakly connected components, as shown in **Figure 6**.

First, to analyze the impact of the size of nodes with following relationships in the SRN on the spread of information, the network size of the k-core decompositions of the SRNs was examined using **Eq. 3**. Our results showed that the network size of R_k–R_k was smaller than that of NR_k–NR_k in the five fake news categories of society, health, disaster, politics, and science. For example, in society-related fake news, $R_k - R_k\,(Size = 0.545) < NR_k - NR_k\,(Size = 0.647)$. In contrast, in business-related fake news with a better debunking effect, the network size of $R_k - R_k\,(Size = 0.340) > NR_k - NR_k\,(Size = 0.234)$.

Second, we also found that the number of weakly connected components in the k-core decompositions of the SRNs differed between the business-related fake news and the other five types of fake news. Specifically, the number of weakly connected components of R_k–R_k was smaller than that of NR_k–NR_k in the five fake news categories of society, health, disaster, politics, and science. For example, in health-related fake news, $R_k - R_k\,(Nwcc = 9) < NR_k - NR_k\,(Nwcc = 16)$. In contrast, in business-related fake news that had a better debunking effect, $R_k - R_k\,(Nwcc = 11) > NR_k - NR_k\,(Nwcc = 9)$.

DISCUSSION

Our results are intended to highlight the differences in the growth rates between DPs and NDPs under different fake news topics from the perspective of SRNs on social media in China, as well as to deeply explore the reasons for the differences, and provide the following four key insights.

First, as shown in **Figure 2**, our results indicated that the spread of fake news is increasing yearly, similar to the findings reported by Vosoughi et al. [12]. We found that in Chinese social media, people have unique preferences for fake news on different topics. To be specific, our results showed that society- and health-related fake news were highly important to Chinese society [4], society-related fake news with 15,844 DPs and 15,501 NDPs, followed by health with 4,292 DPs and 3,981 NDPs, which differed from the distribution on Twitter (corresponding to politics, urban legends, business, terrorism, and war, respectively [12]). Thus, on the one hand, our results confirmed that the information-spreading patterns were different between categories of fake news events [96] and that such a pattern was determined by the event attributes [84]. On the other hand, our results confirmed that the differences in their spread in different countries can be attributed to cultural differences, the news media environment, and other environmental factors [97]. Furthermore, as shown in **Figure 3**, our results also showed that the debunking effect of

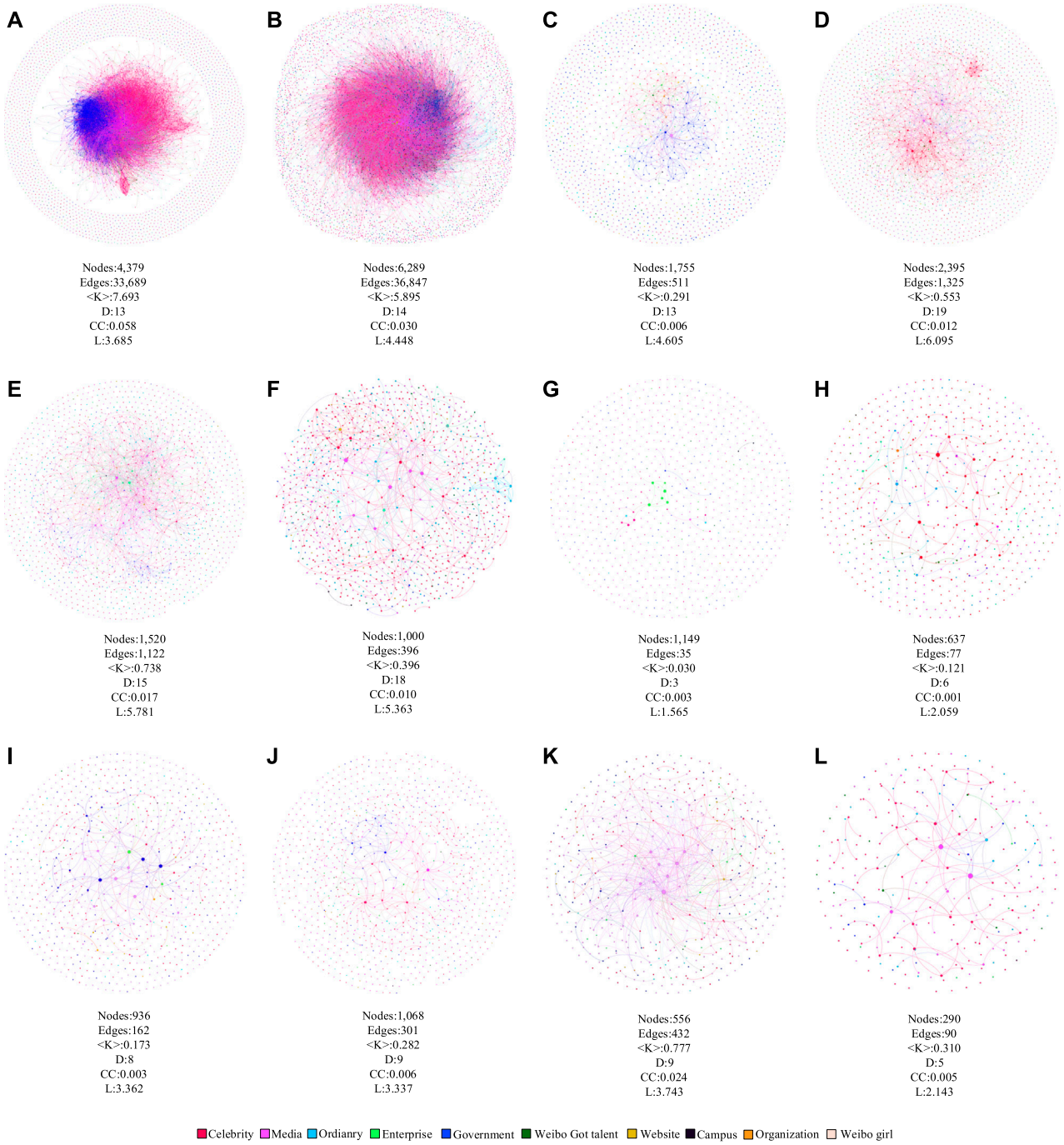

FIGURE 5 | SRNs under six types of fake news: **(A)** of refuters (R–R) in society-related fake news, **(B)** of non-refuters (NR–NR) in society-related fake news, **(C)** R–R in health-related fake news, **(D)** NR–NR in health-related fake news, **(E)** R–R in business-related fake news, **(F)** NR–NR in business-related fake news, **(G)** R–R in science-related fake news, **(H)** NR–NR in science-related fake news, **(I)** R–R in disaster-related fake news, **(J)** NR–NR in disaster-related fake news, **(K)** R–R in politics-related fake news, and **(L)** NR–NR in politics-related fake news.

business-related fake news was better than that of the other types of fake news. This finding is not consistent with those in previous research on fake news on Twitter, which found that falsehood diffused significantly farther, faster, deeper, and more broadly than the truth in all categories of information, and the effects were more pronounced for false political news than for false news about terrorism, natural disasters, science, urban legends, or financial information [12]. In contrast, in our findings, business news had a high p_r value in DPs, which reflected the idea that enterprises had a high industry sensitivity in terms of fake news on Chinese social media platforms. For the other five types of fake news, especially for science- and politics-related fake

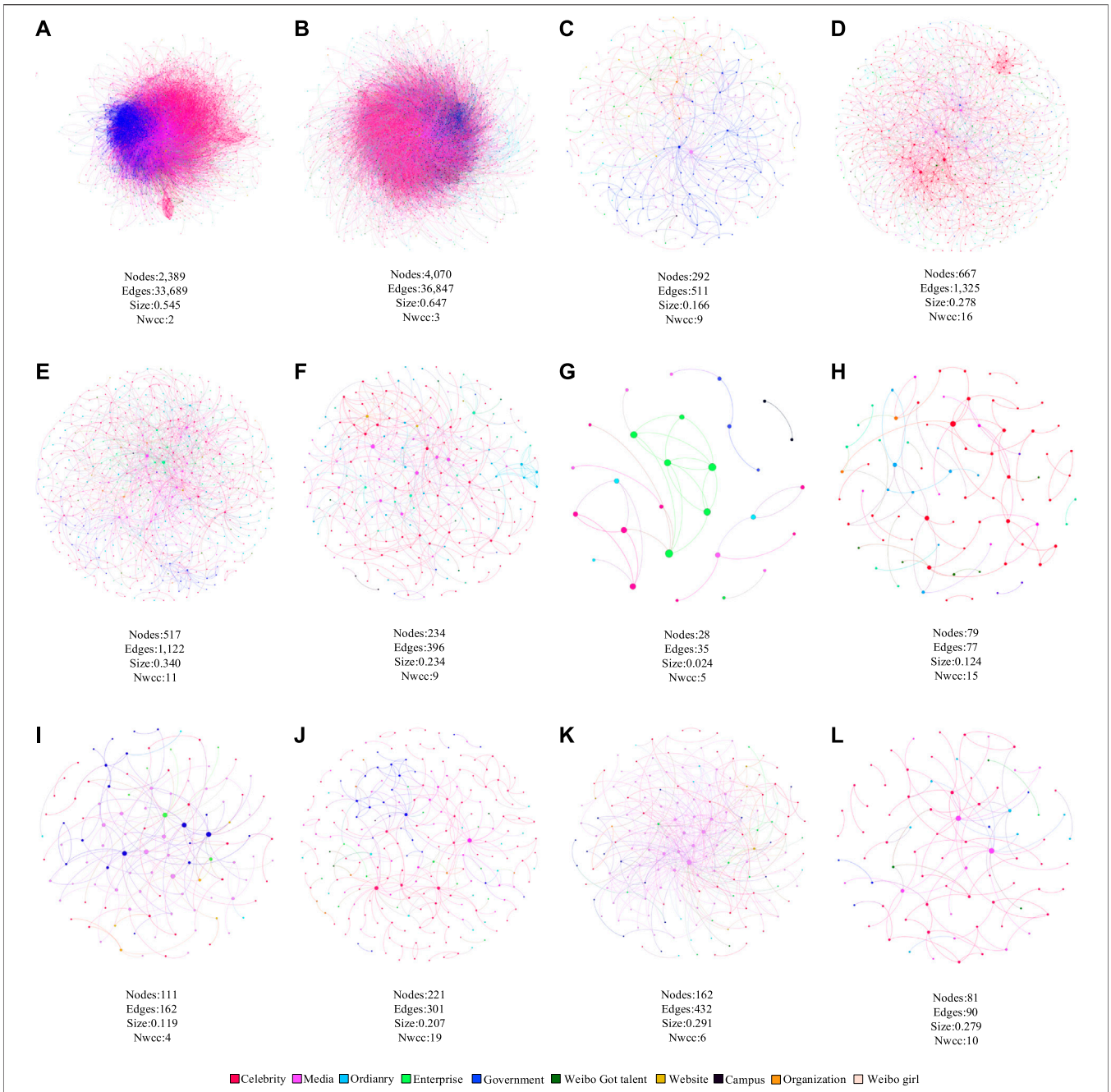

FIGURE 6 | *k*-core decompositions of SRNs under six types of fake news: **(A)** SRN of refuters after *k*-core decomposition (R_k–R_k) in society-related fake news, **(B)** SRN of non-refuters after *k*-core decomposition (NR_k–NR_k) in society-related fake news, **(C)** R_k–R_k in health-related fake news, **(D)** NR_k–NR_k in health-related fake news, **(E)** R_k–R_k in business-related fake news, **(F)** NR_k–NR_k in business-related fake news, **(G)** R_k–R_k in science-related fake news, **(H)** NR_k–NR_k in science-related fake news, **(I)** R_k–R_k in disaster-related fake news, **(J)** NR_k–NR_k in disaster-related fake news, **(K)** R_k–R_k in politics-related fake news, and **(L)** NR_k–NR_k in politics-related fake news.

news, the growth rate of the p_r of DPs was slower than that of NDPs. One possible reason can be attributed to the nature of individuals' relationships with their country, society, and national culture, wherein the social norms directly influence the individual's belief system; this supports the existence of confirmation bias [6], which may result in an individual requiring more time to change their preexisting beliefs. Therefore, the control and management of these two categories of fake news should be urgently strengthened by practitioners, and it is necessary to raise the public's awareness in these two areas immediately. From a cognitive perspective, fake news has a strong preemptive advantage in terms of its spread, resulting in a phenomenon called "failure of refutation," despite real information refuting such fake news in the early stages of the

spread. Thus, we propose that practitioners must empower ordinary users to enhance their knowledge and technology in that particular field, which can improve the users' ability to recognize information. For example, government and mainstream media should improve their control and governance programs. This can be accomplished by explaining the truth accurately and increasing the credibility of reliable information by presenting them in clear and concise factual statements to increase the users' ability to recognize the truth and gain immunity to false information, thereby avoiding and overcoming inherent human biases.

Second, for fake news on different topics, the results in **Table 4** showed that regardless of whether the posts were DPs or NDPs, celebrity accounts (*Ratio*) played a significant role in promoting the spread of information [98]. Users perceive social media posts by influencers (e.g., celebrity accounts) as particularly credible and engaging [99, 100]. To be specific, some health-related fake news studies have shown that celebrity involvement can be an effective tool for health organizations to convey their messages to counter fake news [100]. At the same time, some political-related fake news studies have also indicated that celebrities may participate in fake news as propagators or endorsers, their status affords them extended social reach and the ability to greatly influence the fake news propagation and persuasion, such as governments and partisans use fake news for political framing [101]. Celebrities have been studied more at a micro-level (e.g., fake news event-specific) in previous studies; however, our results are more generalizable as they are drawn in the context of various categories of fake news on Chinese social media platforms at a macro level. For our results, a convincing explanation is that, according to social facilitation theory [102], the opinions of influential leaders tend to become dominant and are constantly strengthened by those around them, making their views highly consistent and strong. That is, people typically believe that influential users are naturally right and that obeying such users will grant them safety; this leads them to accept refutable messages from influential rebuttal sources without judgment. Media opinions and information in newspapers, radio, and television are usually not directly presented to the general audience; they need to pass through opinion leaders for personalized interpretation before flowing to the less active part of the population, i.e., "media information—opinion leaders—general audience." Opinion leaders act as "secondary information dissemination hubs" in the spreading process and a conduit of information; they filter and shape news and share their interpretations with others [103]; therefore, they have a profound impact on opinion formation and diffusion [104]. The celebrities on Sina Weibo can be considered opinion leaders [105], and it is clear from the analysis results that they play a crucial role in the dissemination of information. Therefore, we propose that, in debunking, we should improve controlling the spread of fake news by paying attention to opinion leaders such as celebrities, focusing on the review of the information released by them, and effectively gatekeeping this information before it is released. Moreover, opinion leaders, such as celebrities, should take up the role of promoting the importance of debunking fake news and implementing it among the general public.

Third, as shown in **Figure 6**, for fake news on different topics, our results showed that messages were more likely to spread in networks with following relationships, that is, the larger the size of the nodes (*Size*) with following relationships in the k-core decompositions of SRNs, the faster the information would spread. Our results indicated that the wide distribution of nodes promoted the flow of information. Social media (such as Sina Weibo) are information dissemination platforms based on social relationships, where information dissemination and people's social relationships are interrelated and mutually reinforcing. Fake news tends to initially spread to neighbors, friends, and colleagues of the spreaders and then circulate in certain areas and social groups. The breadth and depth of people's SRNs determine the breadth and depth of the information that they obtain and how far the information they spread can reach. At the same time, our results in **Figure 6** also showed that the greater the number of weakly connected components (*Nwcc*), the easier it was to promote the spread of information. Granovetter's weak connection theory illustrates the shortcuts formed by the weak ties in different social circles, which are conducive to the spread of messages across these circles [106, 107]. Our results show that the number of weakly connected components (*Nwcc*) and size of nodes (*Size*) are more effective in disseminating widely, which is in accordance with the results of previous studies [107]. However, most previous studies have focused on single-topic fake news and reached these conclusions, such as the fake news that "iodized salt is radiation-proof" [107], whereas our findings are more general and reliable as they are drawn in the context of the macroscopic spread of various types of fake news on Chinese social media platforms. In addition, according to previous research, the number of very strong ties among interpersonal relationships is small, but the number of ties with low strength is big [108]. For example, on Sina Weibo, two-way following relationships comprise mostly relatives, friends, colleagues, and other strong connections, whereas one-way following relations comprise mostly weak connections with little connection and weak ties; these form the weakly connected component of the SRNs. Therefore, for one thing, we propose making full use of social networks among users in the fake news debunking process to achieve the following goals: first, improving netizens' ability to distinguish between true and fake news, including teaching them how to fact-check information and educating them in media literacy; and second, improving netizens' critical thinking ability and reducing the herding effect caused by their following relationships. For another thing, we propose that to form an effective hedge against the weak ties of NDPs in the process of fake news debunking, multi-departmental, multi-faceted, and multi-directional joint refutations should be established to spread debunking messages in different circles and a linkage mechanism should be formed. Fake news refuters should integrate support from different rebuttal agents, such as government departments, mainstream media outlets, and opinion leaders to pool their efforts to establish a rapid debunking mechanism for online fake news and expand the influence of authoritative news to debunk fake news quickly and accurately. In this way, governments can play an important role in promoting the dissemination of debunking information for fake news through enlarging the channels of right information disclosure, increasing weak tie connections with the public, and shortening the average path length between individuals in the networks [107].

However, we acknowledge that our research has certain limitations, which give way to promising topics for further

research. First, we only analyzed posts on Sina Weibo, which has limitations in terms of data size and multi-platform sources. Thus, we will consider adding the data of other social media platforms, such as those of Baidu Tieba and WeChat. Second, most of our research results are the experimental results of a comparative analysis of users' SRNs. Therefore, in future research, we will consider using simulation methods to enhance the robustness of our research results, such as applying some physical models for further analysis [109]. We will also consider the internal mechanism of the time delays of DPs among different categories of fake news and analyze the reasons why people opt for refuting or accepting the DPs. Thirdly, to understand the large-scale fake news on Chinese social media platforms, although we focused on the comparison of differences between the debunking and non-debunking of fake news across various topics and obtained some general and reliable findings based on a large-scale multi-category fake news dataset, some of the findings in our results were validation of some intuitive results or previous studies. In the future, by investigating different types of fake news on Chinese social media platforms, we hope to find more interesting and surprising results based on social relationship networks. For example, previous research indicated that structural positions stratified by such variables as gender, age, ethnicity, paid employment, educational attainment, income, and family responsibilities may shape the formation of social relationships and one's ability to gain valuable information [110]. Therefore, in the future, we hope to do more insightful investigations on how the attributes of social relationship networks might affect the spread of debunking information. Finally, to highlight the research objective, we detected only two stances. In a future study, we will consider a more detailed refutation method based on multiple classifications using deep learning algorithms, not only by evaluating the true and false labels of fake news but also by combining concepts such as sociology, psychology, and communication theory to focus on controversy detection, degree of divergence, and group polarization. We will also consider using fake news data on the COVID-19 epidemic for an in-depth study.

CONCLUSION

The growth in social networking has made social media platforms such as Sina Weibo a breeding ground for fake news. Based on the six types of fake news spread on Sina Weibo, first, in this study, we investigated the differences in the volume and growth rates of posts between DPs and NDPs by comparing them in terms of their number and cumulative probability distribution. Second, we used three indices to explore the network characteristics of the following relationships of refuters and non-refuters, namely the proportion of account types, the network size of k-core decompositions of SRNs, and the number of weakly connected components, to uncover the deeper reasons for the differences in the growth rates of DPs and NDPs. Our results showed that the debunking of business-related fake news was better, that of society-related fake news, the most widely spread type of fake news in China, was poor, and that of science- and politics-related fake news, was the worst. Additionally, regardless of whether the posts were DPs or NDPs, a higher number of celebrity accounts, larger sizes of nodes with following relationships in the SRNs, and a higher number of weakly connected components would lead to a faster growth rate of dissemination. Finally, based on the aforementioned results, we examined the reasons for the differences in the growth rates of DPs and NDPs and proposed countermeasures and recommendations for fake news debunking management that can be followed and implemented by government and decision-making institutions.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusion of this article will be made available by the authors, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

XW: Conceptualization, Methodology, Software, Visualization, Formal analysis, Data Curation, Writing. FC: Methodology, Formal analysis. NM: Methodology. GY: Conceptualization, Writing, Funding acquisition.

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