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REVIEW

Studying opinion polarization on social media

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Abstract: Opinion polarization on social media raises a lot of concerns today. In this study, the author provides a systematic review of publications about the issues since 2013 to show the achievements in the existing research on the topic, to sort out the relevant knowledge, and to provide some inspirations for future research in this area. This paper finds that opinion polarization on social media is initiated by three patterns of factors: increasing the homophily in discussions, increasing conflict in social media discussions, and facilitating the spread of misinformation. It also summarizes the existing findings on how to detect and measure opinion polarization in social media, and comes up with opportunities for further researches on this topic.

Keywords: opinion polarization, social media, systematic review

1 Introduction

Media, known as the Fourth Estate, has the power to influence individual beliefs, attitudes, and behaviors [1], and it is widely considered crucial to the democratic process [2]. Benefiting from the internet's improved capacity of handling two-way interactions, social media gains popularity in the recent decades and transforms the ways people obtain, create and share information substantially. It empowers people to customize their information sources and spread their information among the public conveniently. While social media was once the domain of younger, tech-savvy consumers decades ago, it is now commonly used by the mainstream and is used for propaganda extensively [3]. Today, social media have become one of the major forums for information and discussion. According to the Pew Research Center, 68 percent of Americans get information from social media in 2018 [4]. Both mainstream politicians and extremist groups use social media, such as Facebook and Twitter, to get connect to people, spread their propositions, arouse attention and win support [5].

Some scholars once predicted that the internet would promote balanced and judicious public opinion by diversifying the marketplace of ideas and providing an open forum for discussions [6]. Social media, as an internet-based communication platform, fills people with great hope on increasing consensus and bridging differences in opinions. However, the prediction is refuted by heterogeneous and bimodal distributions of opinions on several controversial issues today, including vaccination [7], climate change [8], and political elections [9]. Furthermore, it is indicated that social media can terminate vibrant discussions across opinions because it facilitates participation in like-minded online groups that provide a self-selected refuge for political extremists [10]. Interacting in such online groups will incline participants' predilections towards yet more extreme positions, intensifying conflicts and polarization of opinions in the society.

The term "polarization" in social science origins from the phenomenon of "group polarization". Group polarization, a concept emanating from social psychology, refers to the tendency for a group to make decisions that are more extreme than are the initial inclinations of its members [11]. The phenomenon also holds that individuals' initial attitudes towards a situation will be strengthened and intensified after a group discussion, since the discussion often involves people of like minds [10]. Opinion polarization can have significant harmful societal effects. It can lead to inaction, since "my way or the highway" ideologically rigid mentalities lower the probability of achieving the kinds of compromise that is integral to a healthy democratic society [12]. More seriously, opinion polarization can mobilize members of a society to engage in socially detrimental actions, such as hate speech against vulnerable communities [13], misinformation [14], even terrorism [15].

Given this potential impact, opinion polarization on social media has raised much concerns among scholars in fields such as communication studies, psychology, sociology, politics and information studies. To date, there have been over 200 academic papers published in various outlets. Most of the previous studies describe how opinion polarization happens on social media in certain circumstances, modelizes the process, and tries to explain it with existing theories. There are also some works focusing on defining and detecting opinion polarization on certain social media platforms. However, there is few efforts on reviewing and synthesizing the existing findings in this field, which provides an overview and identifies the achievements and inconsistencies in the prior scholarship. In addition, the available knowledge needs to be synthesized and research gaps needs to be addressed to identify new and pressing issues concerning opinion polarization on social media [16].

In this study, the author responds to the issues above by providing a systematic review of publications about opinion polarization on social media in major journals and conferences since 2013. The study applied the method developed and adopted by Okoli and Schabram [17] and Cao et al. [18] to analyze and summarize the prior scholarship. By developing a systematic review, the author seeks to identify the latest progress of the research, its current research focus, valuable insights in the research and promising areas that require further investigation. Findings of this study achieves two goals: (1) figuring out the factors that facilitate the occurrence of opinion polarization on social media; (2) summarizing the approaches of detecting and measuring opinion polarization in social media.

The paper is organized as follows. It first describes the methodology used for collecting, selecting and analyzing the publications. It then presents a descriptive analysis of the publications selected. After that, it summarizes the current findings of research on this topic and attempt to answer the questions above. Finally, it identifies opportunities for future research and offers a brief conclusion.

2 Methodology

The methodology involves performing a systematic review, a systematic, explicit, and reproducible method for identifying, evaluating, and synthesizing the existing academic works in a field [17]. Systematic review is "a type of literature review that uses systematic methods to collect secondary data, critically appraise research studies, and synthesize findings qualitatively or quantitatively" [19]. It supports the creation of taxonomies and common nomenclatures for a field, the identification of areas that have been thoroughly investigated and those that need more attention, and the discovery of new research opportunities [20]. Although the systematic review method has, in the past, been applied infrequently in library and information science (LIS) research, its use appears to be increasing in information science [21, 22], archive studies [23] and library science [24]. In this study, the author first decides the inclusion and exclusion criteria for paper selection and the search strategies of paper retrieval. Then the author retrieves all the studies within the predefined search range, selects those meet the criteria for further analysis, and then systematically reviews them to extract the information he needs. Finally, the author synthesizes the extracted information to answer the research questions. Details regarding the approach used for searching, the criteria for article selection, and the process of data extraction are described in the following subsections.

2.1 Approach to searching for articles

The author uses keywords and key phrases such as social media, digital media, polarization, opinion polarization, and political polarization as well as the names of major social media applications such as Twitter, Facebook and Weibo to search for articles published after January 2010.The cut-off date is set considering that most studies on social medias are published after that time based on the author's pre-study. The retrieval is conducted with the search engine on Web of Science, a website which provides subscription-based access to multiple scholarly databases. Web of Science is integrated with the UCLA library and therefore provides thorough coverage of all common databases, such as ACM Digital Library, SAGE Journals and Springer. To ensure the retrieval accuracy, the author uses the advanced search option in the search engine. The search strategy is constructed as "TS = ((social media AND polarization) OR (digital media AND polarization) OR (social media AND opinion polarization) OR (digital media AND opinion polarization) OR (Facebook AND polarization) OR (Facebook AND opinion polarization) OR (Twitter AND polarization) OR (Twitter AND opinion polarization) OR (Weibo AND polarization) OR (Weibo AND opinion polarization)).

2.2 Criteria for article selection

826 articles are returned by Web of Science. However, the vast majority of the results are potentially inapplicable to the research questions. Thus, the next step is article selection. For inclusion, each article has to meet four criteria: (1) it must address a study or studies that focus

on opinion polarization and social media; (2) it must provide information and/or insights that can help to answer the author's research questions; (3) it was published in a peer-reviewed academic journal or conference; (4) it must be written only in English. Following these criteria, 86 articles are identified for further analysis.

2.3 Process of data extraction

Data extraction represents a crucial phase in the systematic review procedure. At this point, information is systematically taken from each article to serve as the material for the synthesis stage [17]. According to the research questions, the author reviews all the articles and extract specific information from each of them, including the title, methodology, data source, research questions, and findings. The author also highlights the original views, achievements, or inspirations to later studies in each article with a few sentences. All the information is stored in a clean extraction form (see Table 1).

Table 1 An example of the extraction form

Title	Social Media, Network Heterogeneity, and Opinion Polarization
Method	Quantitative
Data Source	A national probability survey carried out in 2012
Research Question	This study tests relationships between social media, social network service (SNS) network heterogeneity, and opinion polarization.
Findings	1. The use of social media is a positive predictor of the level of network heterogeneity on SNSS and that the relationship is mediated by several news-related activities. 2. This study considers 3 different dimensions of opinion polarization: partisan, ideological, and issue.
Highlights	1. The paper shows that political discussion moderates the relationship between network heterogeneity and the level of partisan and ideological polarizations. 2. It indicates that homophily is a key reason of opinion polarization. Decreasing homophily on social media may be helpful to solve the polarization.

2.4 Descriptive analysis of the articles

A descriptive analysis is first conducted on the selected articles of the following aspects: fields, productivity, and citations impact. As an emerging and interdisciplinary topic, opinion polarization on social media has raised concerns among scholars from a lot of fields, including communication, psychology, computer science, sociology, political science and information studies. With their bibliographic information, The author uses the field categories on Web of Science to classify the articles and find that communications pay the most attention to this topic (31 articles), follow by computer science (including all the subfields, 20 articles), political science (7 articles) and library and information science (6 articles), although it should be noted that an individual article can potentially be classified to more than one field. Detailed results are showed in Table 2.

Table 2 Field categories of the selected articles

Field: Web of Science Categories	Record Count	% of the Total
Communication	35	40.70%
Computer Science	20	23.26%
Political Science	7	8.14%
Library and Information Science	6	6.98%
Psychology	5	5.81%
Engineering	4	4.65%
Telecommunications	4	4.65%
Sociology	3	3.49%
Area Studies	3	3.49%
Business	2	2.33%

Figure 1 presents the total number of the selected articles published by every year (2010-2020), and Figure 2 presents the citation numbers of the selected articles by year. The statistics of 2020 were limited to the first half of the year as the analysis is conducted in August 2020. Opinion polarization on social media is an emerging topic in academia, in terms of both productivity and impact. As shown in the two graphs, the number of new publications and the number of times they are cited have grown rapidly since 2016, indicating that this topic is gaining more and more attention and attracting increasing participation within academia. This may be partly because of the unexpected role that social media and polarization played in the 2016 president election in the United States.

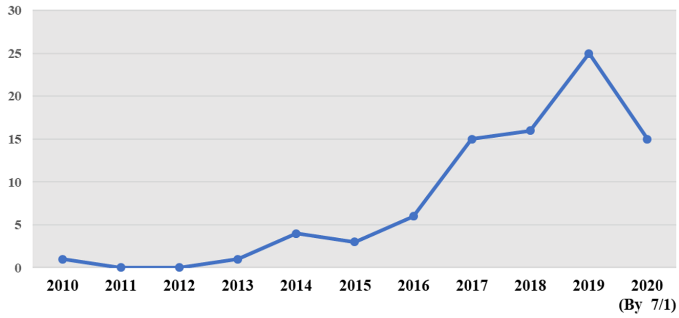

Figure 1 The number of selected articles by year

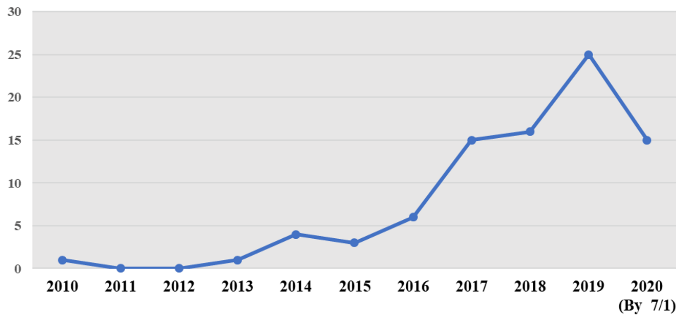

Figure 2 The citations of selected articles by year

3 Results

3.1 Factors that facilitate the occurrence of opinion polarization on social media?

With the rise of social media and the resulting increase in opinion polarization, scholars have developed more knowledge about what factors facilitate opinion polarization on social media. The articles analyzed for this study reveal three different patterns of such factors.

The first pattern involves papers focusing on specific attributes that enhance homophily in online discussion. Homophily, meaning the positive relationship between the similarity of two nodes in a network and the probability of a tie between them [25], is regarded as an important reason for opinion polarization, especially polarization in a group [26]. It is noted by many social scientists as a key reason for increasing opinion polarization on social media [27–29]. Hart et al. [28] show that discussion in homogeneous online social networks increases opinion polarization between liberals and conservatives by intensifying conservatives' opinions. In a study of online link-sharing in the context of climate change, Itkonen [30] shows that Facebook users tend to have online friends who share their concerns. Previous studies have found that social media can increase homophily in them from several approaches. Firstly, some scholars indicate that a possible reason for the increasing homophily on social media is the particular organization of social networks in the new media [31,32]. Social media break down geographical or demographic barriers between people, thereby enormously enlarging their social pool and allowing people to preferentially enter into contact with people sharing very similar ideas and socio-cultural traits [33]. Furthermore, as social media makes it easy to join or quit a discussion group, users may tend to leave a discussion instead of take corrective actions when they find the discussion is becoming polarized, eventually making polarization in a discussion group unstoppable [26]. These, of course, increase the homophily on social media. Secondly, some scholars argue that another possible reason the increasing homophily on social media is selective exposure. Different from traditional media, social media users can select what they want to read or convey from a wide range of sources [34]. However, several studies have proved that people tend to selectively read or convey attitude-consistent information on social media [35–37], which undoubtedly will add to homophily on social media [37]. In addition, in an environment of self-selected media, a deliberative group discussion will produce not a moderate central consensus but opinion convergence at the extremes [38]. Thirdly, other scholars argue that filtering algorithms were another reason for the increasing homophily on social media. Eli Pariser's "filter bubble" hypothesis indicates that social media companies use filtering algorithms to connect users with ideas they are already likely to agree with, thus creating echo chambers of users with very similar beliefs that add to homophily on social media [39]. The hypothesis is later proved by Berman & Katona [40] and Chitra & Musco [41].

The second pattern involves papers focusing on the factors that enhance conflicts on social media. A previous study has shown that exposure to diverse communication networks can increase tolerance and awareness of opposite side's arguments [42]. However, this is not always the case with social media. On the contrary, as people are accustomed to an online environment of homophily, they are likely to get angry and believe in their own opinions more firmly after they encounter some opposite opinions [43]. This will also cause opinion polarization. Nelimarkka et al. [44] find that common exposure to information does not build bridges between people with opposing perspectives but instead often leads to a display of high animosity towards the other camp. An analysis of Twitter backchanneling conversations during the 2016 United States Presidential elections found that interaction between people expressing an opposing opinion on Twitter was more about confrontation than about real exchange of opinions, thus making Twitter conversations prone to polarization [36]. Previous findings indicate that social media can enhance conflicts from several perspectives. First, as an open forum, it is evitable for people to encounter others holding opposite opinions [45]. In a study on conversational interactions about Catalonia's independence on Twitter, it is demonstrated that the conversations across political lines happen more frequently and last significantly longer than the homogenous ones [46]. Chan et al. also verify that aggressive contents contributed by political opponents on social media can catalyze anger of the opponents and enhance conflicts. It would finally begin a vicious spiral where both sides aggravate tensions and become more and more polarized [47]. Second, the top social media, such as Twitter and Instagram, usually have limitations in length and format in publishing, while audiences often spend limited time in reading social media contents. Therefore, people are only showing their standpoints and emotions via social media, yet seldom provide enough context to let their audiences understand why they take that position [48]. Furthermore, Post [49] indicates that people are likely to have a hostile media perception when encountering information from antagonists, which means people are inclined to assume the information is wrong or unreliable if it comes from anyone they against. It will encourage them to intensify their discursive participation and to use polarizing communication styles to react, which undoubtedly will increase the conflicts and cause polarization. Third, it is demonstrated that online incivility is another key factor that increases conflicts on social media [49]. Anderson et al. [50] find that uncivil comments posted on Blogs can increase perceived bias by intensifying the existing antagonism between different groups, and the upward spiral of hostility will bring polarization to the virtual world. Chan et al. [47], in their study of the contents of Facebook pages about the recent social movement in Hong Kong, also find the circumstances that uncivil contents are more likely to be transmitted through communication between ideologically congruent individuals on social media, which usually will subsequently trigger conflicts.

The third pattern, mainly reflected in the most recent articles, involves articles that investigated factors specifically relevant to misinformation. The flood of misinformation online is a growing concern all over the world [51]. It is verified that the spreading of unsubstantiated rumors will have serious consequences on public opinion, triggering antagonism and polarization [52,53]. In a study on rumors about genetically modified organisms on Weibo, Wang and Song demonstrate the spread of GMO-related rumors on Weibo prompt increasing concerns and debates on the topic [54]. Bessi et al. [52], additionally, find unverified information is more likely to be spread in a homogenous online social network, and it will increase polarization in that network. The virtuality and anonymity of social media makes it an ideal space for the spread of misinformation, for example, through social bots or paid posters. Social bots are computer algorithms that use software to produce content automatically or semi-automatically [55]. They are used to emulate and possibly to try to alter human behavior on political issues. Social bots facilitate the distribution of misinformation in at least two ways: (1) They can monitor user traffic flow and follow circadian rhythms to maximize the visibility of their content [55]; (2) They can do everything a human user can do to generate influence, but faster, at a more massive scale, and at a lower cost [56]. As an example, paid posters, known as "Internet water army" in China, are a large group of people who are well organized to "flood" the Internet with purposeful comments and articles [57]. They are often used in business and entertainment industry. Compared to social bots, paid posters play similar roles in facilitating the distribution of misinformation but are more deceptive and indiscernible [58], as they are run by humans instead of machines. Furthermore, today there are people and technical systems specialized in generating and spreading misinformation to get benefits – what Philip N. Howard has recently called the "lie machine" [59]. These systems came of the public view after the so-called "Russia Gate", and may become a hot topic of future research in this field.

3.2 How to detect and measure opinion polarization in social media?

Opinion polarization is the social process of diverging opinions forming in social groups in a society [60]. Sunstein defines "opinion polarization" as members of a deliberating group ending up at a more extreme position in the same general direction as their inclinations before deliberation began [61]. However, when it comes to discussions on social media, it is challenging to detect and measure opinion polarization. In these studies, most researchers only have access to discussion records after they join the discussion group but have no way to know the inclinations of the social media users before they join. Therefore, when scholars refer to "opinion polarization" in the context of social media, it usually emphasizes the ending state instead of the whole process of opinion polarization. Pursuing this idea, Zakhlebin et al. define [62] "opinion polarization" on social media as a state wherein individuals are separated into sides that have little or no communication with and understanding of each other. Lee & Choi [63], on the other hand, define the concept as a state wherein individuals are showing little tolerance toward different opinions, and they are demonstrating increased favoritism towards in-group members and their own ideas.

After figuring out the concept, the next step is to look into the ways to detect opinion polarization in social media. Articles analyzed in this study present a variety of approaches. One of the approaches is to detect the stance of social media users based on their usage of keywords or hashtags [64, 65]. It is easy to put into practice, but only works when the keywords or hashtags express tendentious connotations clearly. Zakhlebin et al. indicate that opinion polarization can be legibly observed on unimodal projections of artificially created bimodal networks [62]. Based on the findings, they then propose an approach using a pseudo-bimodal model to detect and explore opinion polarization in Twitter communication networks. Belcastro et al. [66] come up with a methodology, called IOM-NN (Iterative Opinion Mining using Neural Networks), to discover the polarization of social media users' opinions during election campaigns characterized by competition between political factions. Alamsyah & Adityawarman [67], taking a different approach, combine sentiment analysis and social network analysis into a hybrid approach to identify opinion polarization. Amin et al. present a model for polarized social networks and an unsupervised algorithm to uncover polarization in Twitter and identify polarized groups [68]. They later evaluate their algorithms and their results using multiple Twitter datasets involving polarization of opinions, demonstrating the efficacy of the approach. In addition to the approaches that detect opinion polarization on social media directly, there are also some indirect approaches. For example, Chan and Fu [69] analyze 1644 Facebook pages about political reform in Hong Kong and characterize a relevance between cyberbalkanization and opinion polarization. They then propose a cyberbalkanization index and indicate that the index can be used to predict opinion polarization.

Measuring opinion polarization is another emphasis in the field. Understanding and measuring polarization is a long-term challenge to researchers from several areas, and is key to tasks such as opinion analysis [70]. Articles analyzed in this study proposed two main groups of approaches to measure opinion polarization: objective approaches and subjective approaches.

Objective approaches aim at quantifying polarization in social media objectively and efficiently. Without needs of subjective judgment, they can be easily applied to algorithms that can analyze large amounts of data automatically [68]. Bramson et al. [71] propose and examine nine disambiguated senses and measures for opinion polarization: spread, dispersion, coverage, regionalization, community fracturing, distinctness, divergence, group consensus, and size parity. Matakos et al. [72] propound a polarization index for quantifying the degree of polarization in the network, taking into account both the network structure and the existing opinions of users.

Subjective approaches still call for researchers to read the sample contents and subjectively measure the extent of opinion polarization. Although it often requires considerable manual work, which can be very resource-consuming, it performs better than objective approaches when analyzing the kinds of unstructured and unpredictable contents found in social media. Among the works analyzed for this study, the author finds no paper that specialized in studying subjective approaches, but this kind of approaches are frequently applied in most of the empirical works. Methods that are mentioned included scoring [28, 52, 73, 74], Likert-type scales [27, 75], coding [46, 76, 77], content analysis [78], and classification [79].

4 Conclusions

The objective of this paper is to provide a systematic review of publications about opinion polarization in social media, to show the achievements in the existing research on the topic, to sort out the relevant knowledge, and to provide some inspirations for future research in this area.

Standing on a systematic review of the previous scholarship, the paper identifies three patterns of factors that influence the occurrence of opinion polarization on social media: increasing the homophily in discussions, increasing conflict in social media discussions, and facilitating the spread of misinformation. Furthermore, the paper synthesizes the existing perceptions of "opinion polarization" in the context of social media, and summarizes the existing research findings on how to detect and measure opinion polarization in social media.

As a result, many opportunities are seen in this research area. In terms of topics, there are still many questions to be answered, such as (1) how does opinion polarization occur in social media? (2) what are the forms that opinion polarization can take in social media? (3) will opinion polarization change as social media evolve? (3) what should content producers, social media providers, and social media users do to address the problem? This paper can add to the small body of "polarization" theory that currently exists in social media, as well as contribute to the studies on "polarization" that are currently taking place in other fields.

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