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Review article

Systematic Literature Review on the Spread of Health-related Misinformation on Social Media

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ABSTRACT

Contemporary commentators describe the current period as “an era of fake news” in which misinformation, generated intentionally or unintentionally, spreads rapidly. Although affecting all areas of life, it poses particular problems in the health arena, where it can delay or prevent effective care, in some cases threatening the lives of individuals. While examples of the rapid spread of misinformation date back to the earliest days of scientific medicine, the internet, by allowing instantaneous communication and powerful amplification has brought about a quantum change. In democracies where ideas compete in the marketplace for attention, accurate scientific information, which may be difficult to comprehend and even dull, is easily crowded out by sensationalized news. In order to uncover the current evidence and better understand the mechanism of misinformation spread, we report a systematic review of the nature and potential drivers of health-related misinformation. We searched PubMed, Cochrane, Web of Science, Scopus and Google databases to identify relevant methodological and empirical articles published between 2012 and 2018. A total of 57 articles were included for full-text analysis. Overall, we observe an increasing trend in published articles on health-related misinformation and the role of social media in its propagation. The most extensively studied topics involving misinformation relate to vaccination, Ebola and Zika Virus, although others, such as nutrition, cancer, fluoridation of water and smoking also featured. Studies adopted theoretical frameworks from psychology and network science, while co-citation analysis revealed potential for greater collaboration across fields. Most studies employed content analysis, social network analysis or experiments, drawing on disparate disciplinary paradigms. Future research should examine susceptibility of different sociodemographic groups to misinformation and understand the role of belief systems on the intention to spread misinformation. Further interdisciplinary research is also warranted to identify effective and tailored interventions to counter the spread of health-related misinformation online.

1. Introduction

The spread of misinformation is not new, dating back at least to the early days of printing. Even the term “fake news”, which has achieved considerable contemporary prominence, was first coined in 1925, when an article in Harper's Magazine, entitled “Fake News and the Public” mourned how newswires were allowing misinformation to disseminate rapidly (McKernon, 1925). The growth of the Internet has, however, initiated a fundamental change. In 2013, the World Economic Forum warned that potential “digital wildfires” could cause the “viral spread” of intentionally or unintentionally misleading information (World Economic Forum, 2013). In the health arena, much concern has focused on the spread of misinformation on immunisation, with social media acting as a powerful catalyst for the ‘anti-vaxxer movement’. By encouraging individuals not to vaccinate their children, this movement has been linked to recent measles outbreaks in countries such as the UK, the US, Germany and Italy (Datta et al., 2017; Filia et al., 2017). The prevalence and persistence of such misinformation justifies a careful and systematic review of published literature on the nature and the mechanisms by which misinformation spreads.

1.1. Defining terminology: what is misinformation?

We first review the distinctions between various terms that relate to misinformation. Following the 2016 US presidential election, the term “fake news” attracted substantial media and scholarly attention. The term overlaps with other forms of misleading information, and especially misinformation and disinformation, all conveying messages,

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stories, theories, or opinions that spread rapidly through social contacts or online media. They differ primarily with respect to intent and mode of spread. Misinformation involves information that is inadvertently false and is shared without intent to cause harm, while disinformation involves false information knowingly being created and shared to cause harm (Wardle and Derakhshan, 2017). Although "fake news" is the term that received most popular attention, it is arguably the most problematic one in terms of definitional rigour. Lazer et al. (2018) described it as fabricated information that mimics news media content, but this does not capture the complexity of the phenomenon, which can include both satire and information created deliberately to mislead as a means to achieve a political or other goal (Wardle, 2017). A recent report by a parliamentary committee in the UK concluded that "The term 'fake news' is bandied around with no clear idea of what it means, or agreed definition (House of Commons, 2019). The term has taken on a variety of meanings, including a description of any statement that is not liked or agreed with by the reader. We recommend that the Government rejects the term 'fake news', and instead puts forward an agreed definition of the words 'misinformation' and 'disinformation'". Since the phrase also has been politicized by powerful figures to discredit certain news media (Vosoughi et al., 2018), we refrain from using the term "fake news" throughout the paper.

While noting these distinctions, in practice it often seems difficult to differentiate these categories because of the problem in ascertaining intent. For example, anti-vaccine propaganda may be spread by those who have a genuine concern, however misguided, about safety, and by those who are using the issue as a tool to undermine trust in particular governments. Thus, unless the intent is clear, we use the term *misinformation* as an umbrella term to include all forms of false information related to health, thereby giving those generating it the benefit of the doubt.

1.2. Misinformation spread – from micro-to macro-level

Before discussing the macro-phenomenon of misinformation spread, we first conceptualize the potential mechanism following Wardle and Derakhshan (2017). Three major components are involved in the creation, production, distribution and re-production of misinformation – agent, message and interpreter (Wardle and Derakhshan, 2017). Our review will look at whether and how existing literature from different disciplines examine the type of actor behind the creation of health-related messages on social media platforms, the descriptive features of the message – the durability and distribution of accurate and misleading information - and most importantly, the interpreter's response and how it contributes to the reproduction of misinformation. At the micro-level, individuals who receive misinformation form judgement about the believability of the message, depending on information source, narrative and context, while the tendency to spread depends on the degree to which receivers suspect such misinformation (Karlova and Fisher, 2013). At the macro-level, we observe patterns of misinformation cascade and characteristics of networks.

Early literature on spread of rumours (circulating stories or reports of uncertain or doubtful truth) identified the "basic law of rumour" – the amount of rumour in circulation will vary with the importance of the subject to the individuals concerned *times* the ambiguity of the evidence pertaining to the topic in question (Allport and Postman, 1947). The link between psychological and cultural dimensions generated intriguing questions on what makes misinformation so easy to spread and so hard to debunk.

According to Allport and Postman (1947), the ambiguity of the message may be due to the receipt of conflicting stories, with no one more credible than another. The concept of credibility, as investigated extensively in communications research, encompasses message credibility, source credibility, and media credibility (Metzger et al., 2003). With traditional media, each aspect of information credibility is relatively well understood, although even there some caution is needed. In contrast, with social media, it is particularly challenging to assess the source credibility, as users themselves are the self-publisher, subject to no form of factual verification or accountability. We do know that people regard information from the internet as being as credible as conventional media such as television and radio, but not as that from newspapers (Johnson and Kaye, 1998; Kim and Johnson, 2009). Many studies have thus analysed the credibility of user-generated contents and the cognitive process involved in the decision to spread online information on social and political events (Abbasi and Liu, 2013; Castillo et al., 2011; Lupia, 2013; Swire et al., 2017). This research has highlighted the importance of source credibility and persuasiveness as factors affecting the susceptibility of users to the messages conveyed. Other relevant studies have focused on important concepts such as misperception and confirmation bias, whereby people's views on factual matters are strongly influenced by prior beliefs (Taber and Lodge, 2006; Nyhan and Reifler, 2010; Jerit and Barabas, 2012); polarization within networks (Lewandowsky et al., 2012); and the combined effects of these phenomenon facilitated by social media (Del Vicario et al., 2016; Boutyline and Willer, 2017; Shao et al., 2018). While much of the existing literature has examined social and political issues, we focus on misinformation related to health and wellbeing.

1.3. Misinformation and health: gaps in the evidence base

There is limited understanding of why certain individuals, societies and institutions are more vulnerable to misinformation about health. This is perhaps surprising, as health promotion and public health researchers now pay considerable attention to the potential of the internet as a tool to diffuse health-related information (Chew and Eysenbach, 2010; Ritterband and Tate, 2009; Murray et al., 2009; Scanfeld et al., 2010; Signorini et al., 2011), employing smart phones and other mobile technologies in preventative interventions (Abroms et al., 2013; Eng and Lee, 2013; Free et al., 2013; Steinhubl et al., 2015). Although the internet provides immense opportunities, it also lowers the cost of generating and disseminating information, allowing misinformation and sensationalized stories to propagate. What was once spread locally can rapidly become global, with ideas no longer confined or delayed by geography. This has generated a series of studies of information diffusion (Serrano et al., 2015), rumour spread (He et al., 2015), and consequent behavioural changes (Salathé and Khandelwal, 2011; Wakamiya et al., 2016). These generally employ sophisticated modelling and simulation techniques to identify the rumour propagation dynamics. However, this is still in its infancy and one recent systematic review of behavioural change models found that most papers investigating spread of health-related information and behavioural changes are theoretical, failing to use real-life social media data (Verelst et al., 2016). The literature on misinformation spread is growing, but spans disparate disciplines, including communication studies, epidemiology, psychology, and computational science. We contend that it is now necessary to integrate the different perspective and methodologies, to understand the characteristics of susceptible populations and to devise interventions that are most effective in countering this spread.

To address this gap and provide a comprehensive view on the available evidence, we undertake what is, to our knowledge, the first systematic review of studies that investigated the health-related misinformation content on social media and how it spreads online. We include papers stemming from different disciplines and we analyse them on different dimensions.

First, we identify the main health-related topics where misinformation tends to spread and the descriptive features of misinformation. By focusing on the content and the spread of different health-related misinformation, we reveal a broad landscape of issues that attract actors to espouse misleading claims. The findings shed light on the extent to which different topics are identified and investigated in the literature. This approach can inform those working in these areas.

This seeks to inform social scientists, psychologists, and experts in other fields working to understand this issue, who may otherwise overlook the range of theories that underpin the work of researchers seeking to conceptualize the spread of misinformation. As this is a phenomenon that can be examined from many different perspectives, we have undertaken a co-citation analysis to assess the extent to which different disciplinary paradigms are informing each other, thereby facilitating future interdisciplinary research that can contribute to a more inclusive theoretical framework.

We then explore the existing theories used to explain the phenomenon and undertake a co-citation analysis to ascertain the extent to which ideas spread among disciplinary communities.

We further discuss the different empirical strategies adopted in the analysis. In doing so, we identify the social media platforms where the authors obtain the empirical data, how they incorporate different statistical models to interpret the data, and the empirical progress in our understanding of the mechanism. We conclude by examining the potential for future interdisciplinary research and practical interventions to counter misinformation spread.

2. Methods

2.1. Design and search strategy

Our reporting strategy follows the PRISMA guidelines (Moher et al., 2009). We searched PubMed, Cochrane, Web of Science (WoS) and Scopus for records published between January 2012 and November 2018, using the following search terms in title and abstract:

(i) [misinformation OR fake news OR disinformation OR rumo* OR false OR mislead*]

AND

(ii) [online OR social OR media OR news OR twitter OR Facebook OR google]

AND

(iii) [spread OR propagate* OR disseminat* OR circulat* OR communicat* OR diffuse OR broadcast]

AND

(iv) [health OR disease OR infectious OR virus OR vaccin* OR Ebola OR Zika OR measles]

This yielded 206 records from PubMed, 33 records from Cochrane, 341 records from Web of Science, 51 records from Scopus and 62 records from Google (Fig. 1.). We identified and removed duplicates, which resulted in 651 records that were first screened based on title, abstract, and keywords and then using full-text where necessary. All eligible references were uploaded into reference management software (Mendeley) for assessment of eligibility.

2.2. Screening and eligibility assessment

Next, we screened the results of the 651 records based on title and abstract. Articles that were not original, not involving social media, not related to health, not in English and not on human subjects were excluded. At this, and the subsequent stage, we also excluded the very extensive literature on individual cognitive biases, which would be well beyond the scope of a single review. Similarly, we excluded research on static group decision-making, which can create misinformation (e.g. the phenomenon termed groupthink), that subsequently spreads.

This left 131 potentially eligible papers, which were subject to full-text analysis, applying the following pre-specified eligibility criteria:

Misinformation. Only records that concern misinformation, disinformation, fake news, rumour or any form of information disorder were included.

Social media. Misinformation had to be propagated through online media.

Health. Only records related to disease, treatments, public health and wellbeing were included.

Model or empirical. Modelling (e.g. epidemiological, rumour spread) studies or empirical analysis of the distribution or the dynamic effect of misinformation.

Humans. We are interested in humans and behaviour of humans, and therefore excluded studies about animals and plants.

Original research. We excluded review articles and editorials.

Language. We excluded articles written in languages other than English.

Finally, we excluded papers that lacked analytic rigour or did not incorporate misinformation as the main component of the analysis, which resulted in 57 articles. The PRISMA (Fig. 1) shows the results of these exclusions.

2.3. Data extraction

For the 57 included studies, we analysed the following elements in the full-text: (i) health-related issues and findings; (ii) theoretical framework (if any) and disciplines; (iii) study design.

2.4. Co-citation analysis

To gain further insights on the disciplines contributing to this increasing area of research, we conducted a co-citation analysis of eligible articles to measure the frequency with which two sources are cited together by other documents. Co-citation analysis yields insight into potential disciplinary siloes and theoretical or methodological gaps in the literature. This was possible with 121 of the papers because 10 articles were not indexed on Scopus, where we extracted citation data from.

3. Results

Fig. 2 shows the number of potentially eligible articles by year. Not surprisingly, the number of studies that investigated health-related misinformation increased over the years, from 7 in 2012 to 41 in 2018 (November) with a sharp rise in 2017. The trend implied the growing scholarly interest in the social phenomenon, potentially amplified by major political events in 2016. We exclude certain articles (n = 74) due to their lack of analysis or interpretation of misinformation as mentioned above, and the remainder of this result section relates only to the 57 remaining papers after full-text analysis.

Key features of the studies included are in the web appendix. We first investigated what health-related topics have been studied in relation to misinformation. The largest category relates to communicable diseases (n = 30), including vaccination in general (8) and specifically against Human Papilloma Virus (HPV), Measles, Mumps and Rubella (MMR) and influenza (3, 2 and 1 respectively), as well as infections with Zika virus (9), Ebola (4), influenza (1), Middle East Respiratory Syndrome (1) and Nile Virus (1). Many articles concern chronic non-communicable diseases such as cancer (3), cardiovascular disease (3), psoriasis (1) and bowel disease (1). Some also address issues of diet and nutrition (3), smoking (3) and water safety or quality (2). Five studies cover a broad range of health-related misinformation or rumour online, while the remaining studies were placed in a miscellaneous category, addressing other specific diseases, health problems or medical interventions (Fig. 3). We now briefly describe each of these in turn.

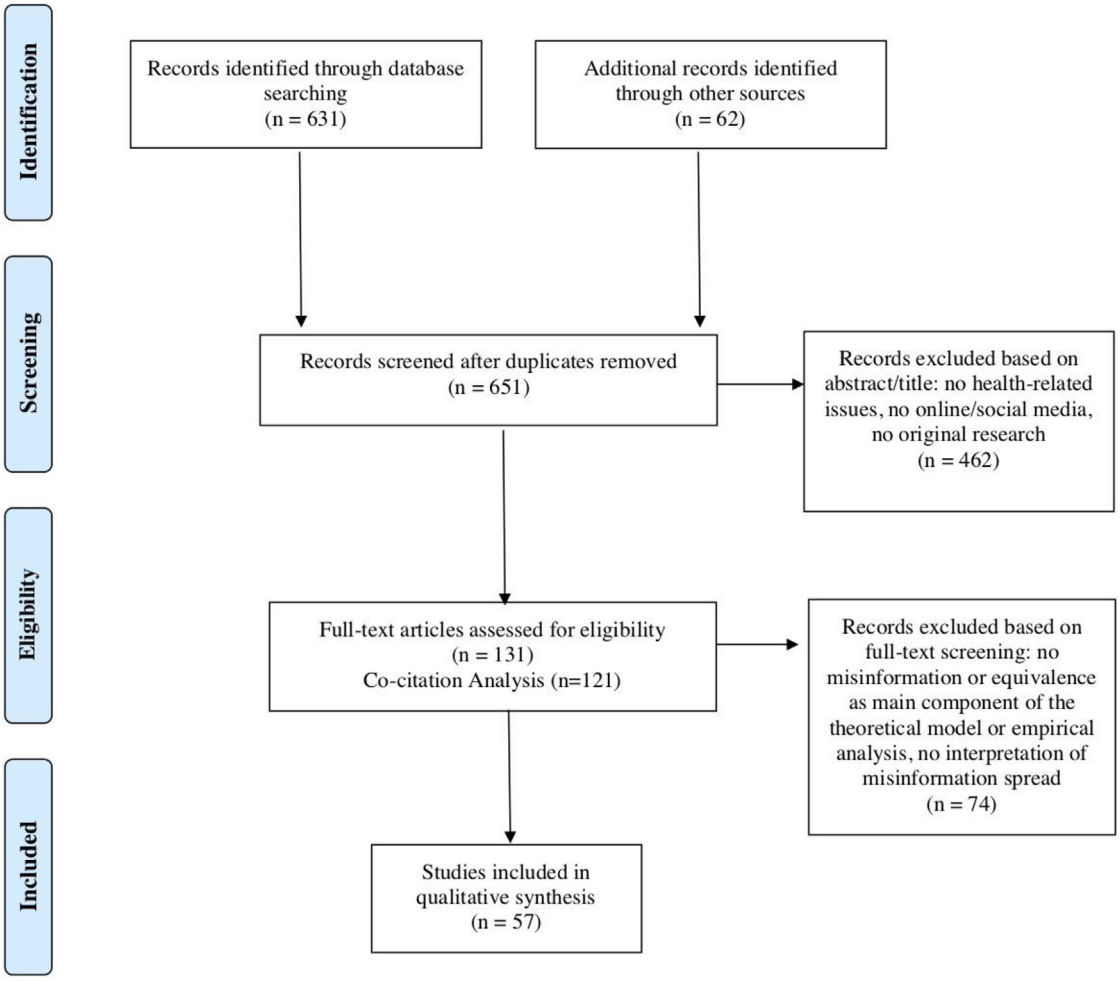

Fig. 1. PRISMA flow diagram.

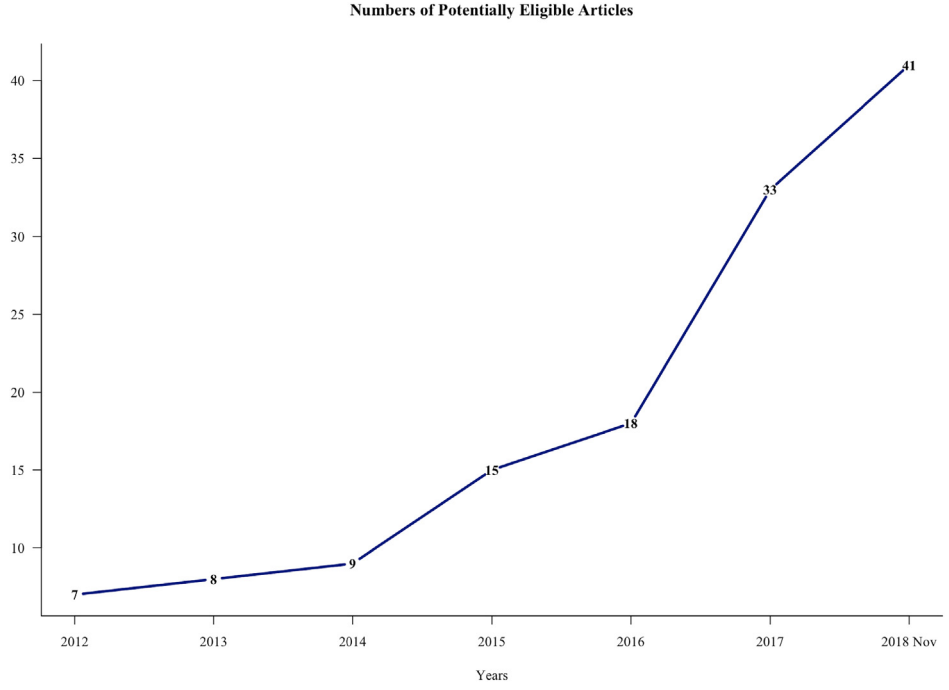

Fig. 2. Numbers of potentially eligible articles.

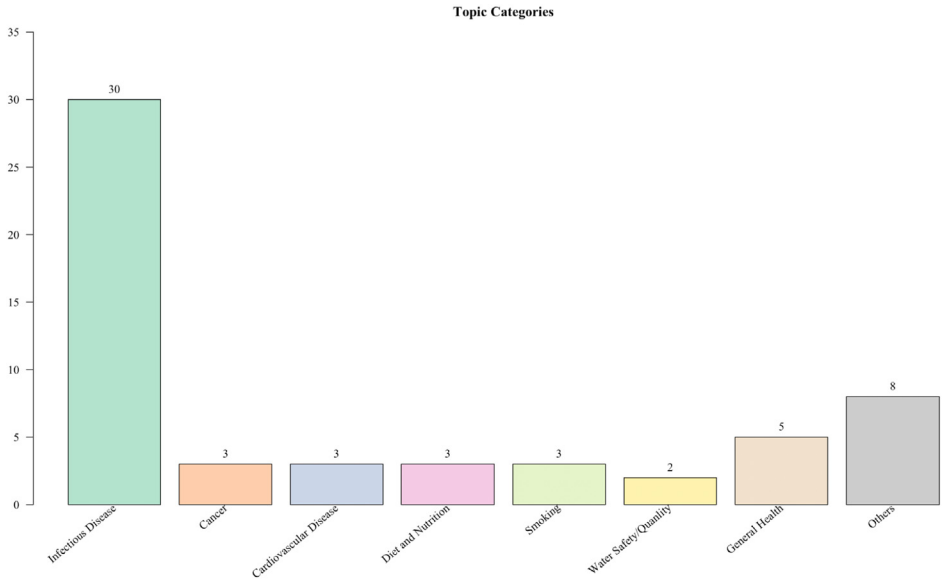

Fig. 3. Topic categories.

3.1. Health-related issues and findings

3.1.1. Vaccines and communicable diseases

Vaccine uptake, especially in children, has fluctuated in recent decades in many developed countries, with marked declines during certain periods. In 2012, the journal *Vaccine* devoted a special issue to "The Role of Internet Use in Vaccination", analysing some of the communication strategies used by both the anti-vaccination movement and public health professionals. Authors recommended comprehensive, structured, and easily understandable responses to anti-vaccination messages (Betsch and Sachse, 2012; Kata, 2012; Reyna, 2012; Nicholson and Leask, 2012). Although refusal of vaccination and movements opposing vaccines date back to the time of Jenner, publication of fraudulent research linking the MMR vaccine to autism and bowel disease (Wakefield et al., 1998) was a seminal moment. The concerns raised then, although long since discredited, have been widely disseminated on social media and even now are highly influential among some groups. For instance, Basch et al. (2017), Donzelli et al. (2018) and Porat et al. (2018) report high online prevalence and popularity of autism-related discussions in fora on vaccination. Tustin et al. (2018) and Xu and Guo (2018) also reported widespread misinformation about side effects, as well as mistrust in government or pharmaceutical companies in discussions on vaccination. Krishna's (2017) study of active propagators of these messages found that those who were knowledge-deficient and vaccine-averse exhibit higher levels of activity than those who are not. Aquino et al. (2017) reported a significant inverse correlation between MMR vaccination coverage and online searches and social network activity on "autism and MMR vaccine". Taken as a whole, the research identifies anti-vaxxer and members of online communities favouring conspiracy theories as sources or propagators of misinformation, with discussions tending to revolve around rhetorical and personal arguments that induce negative emotions (fear, anger, sadness). Although there is less misinformation than accurate information, the former has greater popularity among viewers.

The Zika epidemic stimulated considerable activity on Twitter (Wood, 2018) and Facebook (Sharma et al., 2017), as well as spread of news items (Sommariva et al., 2018), images (Seltzer et al., 2017), and videos (Bora et al., 2018) on a range of media. Conspiracy theories directed at institutions feature frequently in these discussions. For instance, the Zika virus was portrayed as a bioweapon, while rumours spread that the Zika vaccine had been developed to depopulate the earth (Sommariva et al., 2018; Wood, 2018). Conspiracist ideation played a crucial role in one's belief in misinformation (Lewandowsky et al., 2013). However, Bode and Vraga (2018) did not find that belief in conspiracies reduced receptiveness to correction of misinformation on Zika virus, although this research generated several important insights for design of interventions to address this issue.

The Ebola outbreak also provided much additional material. For instance, Fung et al. (2016) examined the role of Twitter and Sina Weibo (Chinese microblog, equivalent to Twitter) in spreading rumours and speculating on treatments. Pathak et al. (2015) found numerous misleading videos online concerning Ebola virus disease. Similar to the studies on vaccination, much of this misinformation comes from individuals who are highly active in influencing opinions, and rumours often garner higher popularity than evidence-based information.

3.1.2. Chronic non-communicable diseases

Though most research on misinformation has focused on infectious disease, misinformation on chronic illnesses such as cancer and cardiovascular disease are not uncommon on social media. Okuhara et al. (2017) looked at online discussions with opposing views on cancer screening in Japan, finding that most propagated anti-cancer screening messages. Staying in Asia, Chen et al. (2018a,b) examined the nature and diffusion of misinformation on gynaecologic cancer in China. Chua and Banerjee (2018) found that individuals are more likely to trust and share cancer-related rumours if the rumours are dreadful rather than wishful, and if one has had previous personal experience.

Studies on other chronic diseases mostly speculate on or promote alternative treatments, for example on diabetes (Leong et al., 2017), heart failure (Chen et al., 2013), hypertension (Kumar et al., 2014) and psoriasis (Qi et al., 2016). Again, misleading videos are more influential. In addition, research by Leong et al. (2017) in India found that diabetes videos tailored to South Asians were more misleading than those not culturally-targeted.

3.1.3. Others

Unsubstantiated messages regarding diets and nutrition can have detrimental effects on susceptible individuals. For instance, Syed-Abdul et al. (2013) investigated how anorexia is promoted as fashion and linked to ideas of beauty in YouTube videos, gaining high popularity among young female viewers. Bessi et al. (2015), analysing the diffusion of diet, environment and geopolitics-related misinformation, found that active users are more likely to span a range of categories, and that online groups promoting conspiracy theories tend to exhibit

polarization. Similar patterns are observed in discussions on water fluoridation, as memorably invoked in the 1964 movie Dr. Strangelove. Seymour et al. (2015) analysed the anti-fluoride network online and found that strong ties among the community are obstacles for expert opinions to be accepted. This indicates that social homogeneity may well be the primary driver of content diffusion and clustering. The modelling of rumour spread is therefore informative of the cascades' size and potential intervention designs in countering such spread.

The tobacco industry has a long history of distorting scientific evidence and misleading consumers. Very recently, Albarracin et al. (2018) showed how misleading portrayal of tobacco's health consequences introduces positivity towards smoking. The advent of electronic cigarettes prompted Harris et al. (2014) to examine content and tweet patterns related to an e-cigarette campaign by a local public health department. The misinformation included arguments that divert attention from the products to messages that sought to discredit authorities.

A few studies have investigated specifically the psychology of individuals who believe and share rumours. Chua and Banerjee (2017), in their analysis on epistemic belief and its effect on the decision to share rumour, showed that epistemologically naïve users have higher propensity to share online health rumours. Li and Sakamoto (2015) discovered that exposing individuals to measures of collective opinion, through counts of retweets and collective truthfulness ratings could reduce the tendency to share inaccurate health-related messages. Taken as a whole, the evidence indicates that the motivation to believe and share rumours reflects both individual and collective makings, but the consequences are difficult to predict because of the complex psychological factors involved.

Finally, the group of miscellaneous studies mainly examined specific medical interventions or issues such as drugs (Al Khaja et al., 2018), paediatric disease (Strychowsky et al., 2013), abortion (Bryant et al., 2014), dialysis (Garg et al., 2015), suicide (Li et al., 2018) and multiple sclerosis (Lavorgna et al., 2018). The common sources of misinformation included advertisements or comments related to advertisements (Garg et al., 2015) and patients' anecdotal experiences (Strychowsky et al., 2013). Again, misinformation was more popular than factual messages.

3.2. Theoretical frameworks and disciplines (co-citation analysis)

We next investigated the theoretical foundations in the included studies, but it rapidly became clear that there was no widely agreed approach to this phenomenon, reflecting the broad range of disciplines that have investigated it. The more dominant disciplines and research areas according to the published journals include public health, health policy and epidemiology (n = 14), health informatics (n = 8), communications studies (n = 5), vaccines (=4), cyberpsychology (n = 3) and system sciences (n = 3).

Disciplinary approaches adopted to conceptualize the phenomenon are varied, but primarily fall within the fields of psychology (n = 8) and communication (n = 4), as well as network science (n = 7). While theories in psychology focus on individual-level cognitive response to misinformation and its corrections, frameworks in network and data science characterise the (online) societal mechanisms involved. For instance, Chua and Banerjee (2018), in investigating the online behaviour in the face of health rumours, invoked the seminal rumour theory (Allport and Postman, 1947), which views personal involvement as a common perception that dictates one's decision to spread rumour. Moreover, rumours that are repeatedly circulated can be reinforced and accepted as credible (Rosnow, 1991), and the consequent perceived high credibility can in turn increase intention to trust and share rumours (Shin et al., 2017). This relates to credibility research, which suggests that perceived credibility and can heighten the persuasive impact, especially for internet users who are not motivated to process information (Metzger, 2007; Metzger et al., 2010). Similarly, Ozturk et al. (2015) explored how different social media settings can reduce rumour spread based on rumour psychology research. Others have referred to psychological studies around conspiracist ideation, inoculation theory and social conformity in understanding the mechanism behind health misperception on social media (Bode and Vraga, 2018; Bora et al., 2018; Li and Sakamoto, 2015). Contrastingly, the use of system or network theories are aimed at explaining the patterns of social influence, social learning, social contagion and homophily and polarization processes (Bessi et al., 2015; Radzikowski et al., 2016; Schmidt et al., 2018; Sicilia et al., 2017; Wood, 2018). The framework typically assists the subsequent social network analysis.

Two studies borrowed insights from philosophy – Grant et al. (2015) employed the rhetorical framework to examine the persuasive features of pro- and anti-vaccine sites, while Chua and Banerjee (2017) used the epistemology framework to explore the role of epistemic belief in affecting rumour-sharing behaviour. Finally, situational theory of publics (Grunig, 1997) from public relation studies are adopted to identify vaccine-negative activists (Krishna, 2017). The remaining articles from computational studies and clinical perspectives lack any theoretical underpinning and are purely empirical.

Given that the findings are from disparate disciplines, we conduct the co-citation analysis on all the potentially eligible articles to identify the clusters of disciplinary communities. In co-citation network analysis, the unit of analysis is the cited source, and we include the journals cited at least 5 times within the 121 articles. As seen in Fig. 4, the distance in the map between any pair of journals reflects their similarity to each other (van Eck and Waltman, 2010), and we use the LinLog/modularity normalization technique to minimize the distance between connected nodes (Noack, 2009). The size of the nodes represents the number of citations, and the line indicates the presence of citation in either direction. The analysis identified 4 distinct (inter-)disciplinary clusters, which we assigned as follows (with randomly generated colours, from left to right): Social Psychology and Communications (red), General Science and Medicine (blue), Infectious Disease/Vaccine and Public Health (green), Medical Internet and Biomedical Science (purple). Overall, the literature is concentrated in general science and vaccines/infectious diseases. Psychology and communications literature sit on the periphery, with relatively less cross-citation with the science and medicine literature. Interestingly, we also observe a few sociology journals at the bordering regions between clusters, implying their incipient roles in acknowledging different insights across disciplines. There is potential for greater interdisciplinary collaboration.

3.3. Study design

Turning to research design, most studies employed content analysis (n = 38) either alone or as a component of the analysis, studying various forms of social media (n = 10), YouTube videos (n = 12), Twitter or equivalents (n = 8), websites (n = 5), images (n = 1) or mobile messengers (n = 2). Authors observe the distribution of useful and misleading information, and the pattern of consumption by different users. Some studies incorporated social network analysis or epidemiological modelling to better explain the dynamics of misinformation spread (Bessi et al., 2015; Ghenai and Mejova, 2017; Harris et al., 2014; Jin et al., 2014; Radzikowski et al., 2016; Wood, 2018). Many designs were also complemented by sentiment measures, for instance, the “anti-vaccine” sentiment (Bahk et al., 2016; Xu and Guo, 2018).

Seven studies used experimental designs. Bode and Vraga, in three different papers, manipulated Facebook's “related news” function to confirm or correct (or both) misinformation about the purported link between vaccines and autism, as well as unfounded link between genetically modified organisms (GMO) and health (Bode and Vraga, 2015; Vraga and Bode, 2017). They also simulated Twitter feeds with false information about Zika virus to evaluate the ability of corrective responses to reduce misperception (Vraga and Bode, 2017). Chua and Banerjee (2017, 2018) undertook web-based experiments with

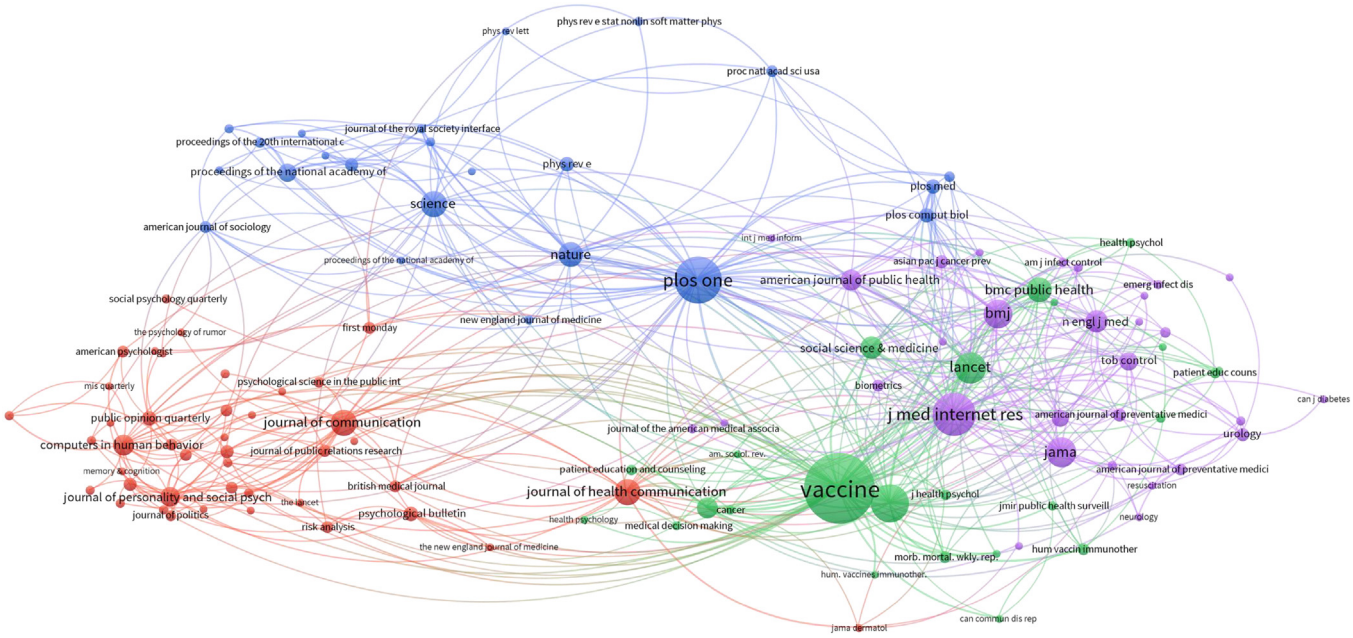

Fig. 4. Co-citation analysis. We extracted citation data from Scopus and analysed citation patterns using network-clustering algorithms in VOSviewer 1.6.8. The network map shows co-citation patterns of 121 journals cited at least 5 times within the studies that are potentially eligible. The node size represents the number of citations, and the lines represent the presence of citation in either direction. We restricted the minimum cluster size to 20, which resulted in 4 disciplinary clusters and 2367 links. We were not able to identify 10 articles because they were not indexed on Scopus, we therefore exclude them for the co-citation analysis.

participants exposed to combinations of rumours and counter-rumours. Ozturk et al. (2015) explored different ways to reduce rumour spread on Twitter using Amazon's Mechanical Turk, an online crowdsourcing platform. Albarracin et al. (2018) used the same platform to evaluate the effects of YouTube videos on viewer attitudes to tobacco products.

A few studies used survey instruments to understand how social media can spread misconceptions about Ebola in West Africa (Adebimpe et al., 2015) and inflammatory bowel disease in the USA (Groshek et al., 2017), and to explore the relationship between knowledge deficiency and negative attitudes towards vaccines (Krishna, 2017). One case-study adopted an anthropological approach and used thick description to review the rhetorical features of both pro-vaccine and vaccine-sceptical websites Grant et al. (2015).

4. Discussion

4.1. Findings

We found that, while there have been studies of the spread of misinformation on a wide range of topics, the literature is dominated by those of infectious disease, including vaccines. Overall, existing research finds that misinformation is abundant on the internet and is often more popular than accurate information. Several of the studies address areas where state action challenges individual autonomy. The classic example is vaccination, where effective protection of the population requires achievement of levels of uptake sufficient to achieve herd immunity. This review confirms that misconceptions about MMR vaccine and autism, in particular, remain prevalent on social media (Aquino et al., 2017; Chen et al., 2018a,b). Other topics share scientific uncertainty, with the authorities unable to provide confident explanations or advice, as with newly emerging virus infections such as Ebola and Zika viruses (Basch et al., 2017; Fung et al., 2016; Sommariva et al., 2018).

The agents that create misinformation are mostly individuals with no official or institutional affiliations. This relates to our initial discussions on credibility – what makes a source trustworthy for readers? Formal institutions are increasingly challenged by the rise of, for instance, “expert patient”, blurring the boundaries between authority and quasi-proficiency (Seymour et al., 2015). Traditional vertical health communication strategies are eroded by horizontal diffusion of conspiracy-like messages. The narratives of misinformation are dominated by personal, negative and opinionated tones, which often induce fear, anxiety and mistrust in institutions (Bessi et al., 2015; Panatto et al., 2018; Porat et al., 2018). When people are frightened and doubtful, they can be more susceptible to misinformation. Once false information gains acceptance in such circumstances, it is difficult to correct, and the effectiveness of interventions vary according to each individual's personal involvement, literacy and socio-demographic characteristics, features that tend to be under-explored in existing research.

The included articles adopted disparate theoretical approaches in conceptualizing the phenomenon, with the dominant frameworks from the fields of psychology and network science. Theories employed in psychology aimed to explain individual-level cognitive response of misinformation and rumour online (Bode and Vraga, 2018; Bora et al., 2018; Chua and Banerjee, 2018; Li and Sakamoto, 2015; Ozturk et al., 2015), whereas network theories focus on the social mechanism and patterns of misinformation spread (Bessi et al., 2015; Radzikowski et al., 2016; Schmidt et al., 2018; Sicilia et al., 2017; Wood, 2018). Further co-citation analysis on all articles that investigated the phenomenon revealed that the disciplinary landscape concentrates around general science and vaccines/infectious disease, while psychology and communication studies have less cross-citation with the science and medicine literature. The sociology discipline has great potential to bridge the different communities.

Researchers have employed increasingly sophisticated analytic techniques for empirical analysis, such as the use of social media data for sentiment analysis. The majority of the articles included a content analysis of the information on social media, ranging from text, images and videos. Several studies employed complexity and network theories to model the dynamics of rumour spread and opinion polarization (Bessi et al., 2016; Jin et al., 2014). Other studies have adopted psychological and linguistic perspectives (Fung et al., 2016; Li et al., 2018; Waszak et al., 2018). While we have excluded research on both

individual and group biases, we feel it is important to note how several studies invoked the concept of *confirmation bias,* concluding that it plays an important role in creating online echo-chambers (Bessi et al., 2015; Donzelli et al., 2018). This highlights the need for much more research on the socio-psychological characteristics of those who believe and propagate misinformation. In particular, there is a need to understand better the roles of both ideology and belief systems (Jost et al., 2018) and what might be termed "lazy thinking" (Pennycook and Rand, 2018). For instance, although the role of literacy and cues to credibility are critical concepts in the design of experiments, they should also be explored in empirical studies, and especially those that use big data from social media platforms.

4.2. Gaps and potential for future research

Although sociology and psychology pioneered research to understand rumour (Allport and Postman, 1947; Bartlett, 1932; Kirkpatrick, 1932), psychologists are only beginning to study the implications of the explosion in internet use (Stone and Wang, 2018). While we conclude from the co-citation analysis that studies on misinformation in health cover a wide range of disciplines, there is a marked lack of interdisciplinary research. This could, for example, allow hypotheses to be generated by social scientists using rumour theory and tested using quantitative analysis of social media data.

While most of the studies recommended courses of action based on their results, only a handful of papers proposed specific and tested interventions to reduce misinformation spread. For instance, Ozturk et al. (2015) discovered that rumour-countering warnings such as "this tweet may contain misinformation" did decrease participants' likelihood of sharing a rumour, consistent with findings in the psychological literature (Bordia and Difonzo, 2004). Bode and Vraga (2018) showed that algorithmic correction (by a platform) and social correction (by peer) are equally effective in correcting misinformation and call for campaigns to encourage users to refuse false or misleading information. The same authors have shown how expert organization can correct misinformation without damaging its credibility, presenting an appealing intervention to reduce misinformation spread (Vraga and Bode, 2017).

Finally, there is a need to characterise the scale and nature of the phenomenon much better, for example with studies of which socio-demographic characteristics make social media users more susceptible to and therefore likely to share health-related misinformation.

4.3. Limitations

Before concluding, we will note several limitations of the systematic review. First, although we have attempted to define the phenomenon we are studying, our search strategy may not capture the terminology used by others. This is not just a problem of language. There are many related phenomena, such as denialism, groupthink, fearmongering, and equivalents in other languages, such as Lügenpresse (lying press) in German and it is possible that these or others may be used, in some circumstances, to describe some elements of what we are studying. Second, even when we agree the terms, such as misinformation and 'fake news', the meanings adopted by authors can vary. Third, as noted at the outset, it is very difficult to ascertain the motives of those spreading particular rumours and myths, leaving us unable to answer the old question "mad or bad?". Fourth, while our focus has been on messages concerning health-related issues, misinformation about other issues can have health consequences. For instance, a man from North Carolina travelled to Washington in 2016 and opened fire at a pizzeria following the spread of what became termed the Pizzagate theory, whereby it was alleged that the pizzeria was the site of a paedophile ring organised by Democratic Party leaders. Even though comprehensively debunked, subsequent polls showed that this allegation was still widely believed. Finally, since we excluded articles that are not published in English, we may have omitted relevant papers published in other languages.

5. Conclusion

Social media platforms, although providing immense opportunities for people to engage with each other in ways that are beneficial, also allow misinformation to flourish. Without filtering or fact-checking, these online platforms enable communities of denialists to thrive, for instance by feeding into each other's feelings of persecution by a corrupt elite (McKee and Diethelm, 2010). The accumulation of individual beliefs in these unfounded stories, conspiracy theories, and pseudoscience can give rise to social movements, such as the anti-vaccination movement, with profound consequences for public health. This is further exacerbated by the fact that it is politically incorrect to question or criticize the belief of others, and the fight for truth is nevertheless against the flow of true believers armed with ignorance and misinformation (Kaufman et al., 2018).

We have shown that academic literature on this social phenomenon mainly revolves around vaccination and infectious disease, drawing on various disciplines, frameworks and empirical methods. Among the articles examined, there is broad consensus that misinformation is highly prevalent on social media and tends to be more popular than accurate information, while its narrative often induces fear, anxiety and mistrust in institutions. The severity and the deleterious effects it may pose on the society is hardly quantifiable, but evidence abounds that we need more research on the identification of susceptible populations, and on the understanding of socio-demographic and ideological asymmetries in the intention to spread misinformation.

Finally, since the persistence of misinformation owes both to the psychological responses and to the social contexts under which misinformation spread, potential interventions should target both fronts. At the individual level, although interventions to correct misperceptions are proven effective at times, efforts to retract misinformation need to be carried out with caution in order to prevent backfiring. This requires profound understanding on how epistemic and ideology beliefs act as obstacles to accepting scientific evidence. A more constructive approach may be to cultivate critical thinking and to improve health and media literacy, thereby equipping individuals with the faculty to critically assess the credibility of information. At the system level, how we can amend our information ecosystem to reduce selective exposure and opinion polarization is not a challenge for academics and policy-makers alone to face. We therefore hope that our review can stimulate social scientists, psychologists, computer scientist and medical professionals to not only collaborate with each other, but also engage with industries and internet consumers to understand and counter the effects of this increasingly important social phenomenon.

Authors' contributions

YW collected the data, performed the review and drafted the manuscript. All authors contributed to the interpretation, writing and editing of the manuscript.

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Appendix Table

Characteristics of Included Studies

Health Issue (by category)	Setting/Geographic Focus	Theory/Framework	Study Design	Platforms	Authors
Communicable Disease					
Ebola	Nigeria	N/A	Survey	Facebook, Twitter	Adebimpe et al. (2015)
Ebola	Chinese and English-speaking Countries	N/A	Content Analysis (Social Media)	Sina Weibo, Twitter	Fung et al. (2016)
Ebola	US	Epidemiological Models	Content Analysis (Twitter); Epidemiological Modelling	Twitter	Jin et al. (2014)
Ebola	English-speaking Countries	N/A	Content Analysis (Video)	YouTube	Pathak et al. (2015)
Influenza	China	Rumour Theory (Psychology)	Content Analysis (Social Media)	Sina Weibo, Tencent Weibo	Chen et al. (2018a,b)
Middle East Respiratory Syndrome	South Korea	N/A	Social Network Analysis	Twitter, Blogs, Online Community Text, Discussion Board Text, News sites	Song et al. (2017)
Nile Virus Infection	English-speaking Countries	N/A	Content Analysis (Video)	YouTube	Dubey et al. (2014)
Vaccination (general)	English-speaking Countries	N/A	Content Analysis (Video)	YouTube	Basch et al. (2017)
Vaccination (general)	Italy	N/A	Content Analysis (Video)	YouTube	Donzelli et al. (2018)
Vaccination (general)	US	Situational Theory of Publics (Public Relations)	Survey	Websites	Krishna (2017)
Vaccination (general)	Spain	N/A	Content Analysis (Twitter)	Twitter	Porat et al. (2018)
Vaccination (general)	English-speaking Countries	Network Theory	Social Network Analysis	Facebook	Schmidt et al. (2018)
Vaccination (general)	Canada	N/A	Content Analysis (Facebook)	Facebook Instagram Twitter YouTube	Tustin et al. (2018)
Vaccination (general)	English-speaking Countries	N/A	Sentiment Analysis	Google	Xu and Guo (2018)
Vaccination (general) + GMOs	US	Psychological Theory	Experiment	Facebook	Bode and Vraga (2015)
Vaccination (HPV)	US	Theory of Rhetorical Situation (Philosophy)	Qualitative Case Study (Anthropology)	Websites	Grant et al. (2015)
Vaccination (HPV)	US	N/A	Content Analysis (Social Media)	Twitter	Mahoney et al. (2015)
Vaccination (influenza)	Italy	N/A	Content Analysis (Website)	Websites, Blogs	Panatto et al. (2018)
Vaccination (MMR)	Italy	N/A	Content Analysis (Social Media)	Google Trend, Twitter, Facebook; National Institute of Health (Istituto Superiore di Sanità)	Aquino et al. (2017)
Vaccination (MMR)	US	Network Theory	Content Analysis (Twitter); Social Network Analysis	Twitter	Radzikowski et al. (2016)
Vaccination (Polio and HPV)	Pakistan, US	N/A	Sentiment Analysis	Mainstream Media, Twitter, Vaccine Sentimeter	Bahk et al. (2016)
Zika Virus	US	Psychological Theory	Experiment	Facebook, Twitter	Bode and Vraga (2018)
Zika virus	English-speaking Countries	Inoculation Theory (Psychology)	Content Analysis (Video)	YouTube	Bora et al. (2018)
Zika Virus	Global	N/A	Content Analysis (Twitter); Social Network Analysis	Twitter	Ghenai and Mejova (2017)
Zika Virus	Global	N/A	Content Analysis (Image)	Instagram flicker	Seltzer et al. (2017)
Zika Virus	US	N/A	Content Analysis (Social Media)	Facebook	Sharma et al. (2017)
Zika Virus	English-speaking Countries	Network Theory	Social Network Analysis	Twitter	Sicilia et al. (2017)
Zika Virus	English-speaking Countries	N/A	Content Analysis (Weibo)	Facebook, Twitter, LinkedIn, Pinterest, GooglePlus, Web links	Sommariva et al. (2018)
Zika Virus	US	Psychological Theory	Experiment	Twitter	Vraga and Bode (2017)
Zika Virus	English-speaking Countries	Network Theory	Content Analysis (Twitter); Social Network Analysis	Twitter	Wood (2018)
Chronic Non-communicable Disease					
Cancer					
Cancer + Diet and Nutrition	US	Rumour Theory (Psychology)	Experiment	Websites	Chua and Banerjee (2018)
Cancer Screening	Japan	N/A	Content Analysis (Website)	Websites, Blogs, Facebook	Okuhara et al. (2017)

Gynaecologic Cancer	China	N/A	Content Analysis (Social Media)	Sina Weibo Tencent Weibo	Chen et al. (2018a,b)
Cardiovascular Disease					
Diabetes + Diet	India	N/A	Content Analysis (Video)	YouTube	Leong et al. (2017)
Heart Failure	English-speaking Countries	N/A	Content Analysis (Video)	YouTube	Chen et al. (2013)
Hypertension	English-speaking Countries	N/A	Content Analysis (Video)	YouTube	Kumar et al. (2014)
Other Chronic Non-communicable Disease					
Inflammatory Bowel Disease	English-speaking Countries	N/A	Survey	Facebook, Twitter, YouTube, Website	Groshek et al. (2017)
Psoriasis + Diet	English-speaking countries	N/A	Content Analysis (Video)	YouTube	Qi et al. (2016)
Others					
Diet and Nutrition					
Anorexia	English, Spanish, Italian and Portuguese-speaking Countries	N/A	Content Analysis (Video)	YouTube, Vimeo and Voeh	Syed-Abdul et al. (2013)
Diet and Health-related Information	Arabic-speaking Countries	N/A	Content Analysis (Twitter)	Twitter	Alnemer et al. (2015)
Diet and Health-related Rumour	Italy	Network Theory	Content Analysis (Social Media); Social Network Analysis	Facebook, Twitter and YouTube	Bessi et al. (2015)
Smoking					
e-cigarette	US (Chicago)	Network Theory	Content Analysis (Twitter); Social Network Analysis	Twitter	Harris et al. (2014)
Hookah Tobacco Smoking	US	N/A	Content Analysis (Website)	Websites, Facebook, MySpace, Twitter	Primack et al. (2012)
Tobacco	US	N/A	Experiment	YouTube	Albarracin et al. (2018)
Water Safety/Quality					
Water Fluoridation	US	N/A	Content Analysis (Social Media)	Facebook, Twitter, YouTube, Website	Mertz and Allukian (2014)
Water Fluoridation	US	Network Theory	Social Network Analysis; Sentiment Analysis	Facebook, Websites	Seymour et al. (2015)
General Health (Rumour Psychology)					
Health-related Rumours	Southeast Asia	Epistemology (Philosophy)	Experiment	Websites	Chua and Banerjee (2017)
Health-related Rumours	US	Rumour Theory (Psychology)	Experiment	Twitter	Li and Sakamoto (2015)
Health-related Rumours	China	N/A	Content Analysis (Wechat)	Wechat	Li et al. (2017)
Health-related Rumours	US	Psychological Theory	Experiment	Twitter, Websites	Ozturk et al. (2015)
Health-related Rumours	Poland	N/A	Content Analysis (Social Media)	Facebook, Twitter, LinkedIn, Pinterest	Waszak et al. (2018)
Miscellaneous					
Abortion	US	N/A	Content Analysis (Website)	Websites	Bryant et al. (2014)
Dialysis	English-speaking Countries	N/A	Content Analysis (Video)	YouTube	Garg et al. (2015)
Drug	Bahrain	N/A	Content Analysis (WhatsApp)	WhatsApp	Al Khaja et al. (2018)
Multiple Sclerosis	Italy	N/A	Content Analysis (Website)	Websites	Lavorgna et al. (2018)
Paediatric Tonsillectomy + Diet	English-speaking Countries	N/A	Content Analysis (Video)	YouTube	Strychowsky et al. (2013)
Suicide	China	N/A	Content Analysis (Weibo)	Sina Weibo	Li et al. (2018)

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