Prevalence of health misinformation in social media: a systematic review

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Prevalence of health misinformation in social media: a systematic review

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Abstract

Background: The propagation of health misinformation through social media has become a major public health concern over the last two decades. Although today there is broad agreement among health professionals and policy makers on the need to control health misinformation, there is still little evidence about the effects that the dissemination of false or misleading health messages through social media could have on public health in the near future. Nor is there sufficient evidence on alternative ways to effectively combat health misinformation online. Before adopting necessary measures, we must first discover which health misinformation topics are most prevalent and which social media platforms are most frequently used to spread them.

Objective: This systematic review aims to identify the main health misinformation topics and their prevalence on different social media platforms, focusing on methodological quality and the diverse solutions that are being implemented to address this public health concern.

Methods: A systematic review was conducted by searching PubMed, MEDLINE, Scopus and the Web of Science for articles published in English before March 2019 with a particular focus on studying health misinformation in social media. Additional studies were identified and selected by searching bibliographies of electronically retrieved review articles.

Results: Health misinformation proved to be more prevalent in studies related to smoking hookahs and other water pipes, e-cigarettes, and drugs such as opioids or marihuana. Health misinformation about vaccines was also very common. However, studies reported different levels of health misinformation depending on the type of vaccine studied with the HPV vaccine being the most affected. Secondly, health misinformation related to diets or pro-ED arguments were moderate in comparison to the aforementioned topics. Studies focused on diseases (i.e. NCDs and pandemics) also reported moderate misinformation rates, especially in the case of cancer. Finally, the lowest levels of health misinformation were related to medical treatments.

Conclusions: Prevalence of misinformation varies according to differences in topics and social media platforms. This systematic review offers a comprehensive comparative framework that identifies the main action areas in the study of health misinformation in social media.

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Prevalence of health misinformation in social media: a systematic review

Abstract

Background: The propagation of health misinformation through social media has become a major public health concern over the last two decades. Although today there is broad agreement among researchers, health professionals, and policy makers on the need to control and combat health misinformation, the magnitude of this problem is still unknown. Consequently, before adopting the necessary measures for the adequate control of health misinformation in social media, it is fundamental to discover both the most prevalent health topics and the social media platforms from which these topics are initially framed and subsequently disseminated.
Objective: This systematic review aims to identify the main health misinformation topics and their prevalence on different social media platforms, focusing on methodological quality and the diverse solutions that are being implemented to address this public health concern.
Methods: This systematic review was conducted according to the Preferred Reporting Items for Systematic reviews and Meta-Analyses guidelines (PRISMA). We searched PubMed, MEDLINE, Scopus and the Web of Science for articles published in English before March 2019 with a particular focus on studying health misinformation in social media. We defined health misinformation as a health-related claim based on anecdotal evidence, false, or misleading due to the lack of existing scientific knowledge. The criteria for inclusion were: 1) articles that focused on health misinformation in social media, including those in which the authors discussed the consequences or purposes of health misinformation; and 2) studies that described empirical findings regarding the measurement of health misinformation in these platforms.
Results: A total of 69 studies were identified as eligible, covering a wide range of health topics and social media platforms. The topics were articulated around six principal categories: vaccines (32%), drugs or smoking (22%), non-communicable disease (19%), pandemics (10%), eating disorders (9%), and medical treatments (7%). Studies were mainly based on five methodological approaches: Social Network Analysis (28%), Evaluating Content (26%), Evaluating Quality (24%), Content/Text analysis (16%) and Sentiment Analysis (6%). Health misinformation proved to be the most more prevalent in studies related to smoking products and drugs such as opioids or marijuana. Posts with misinformation reached 87% in some studies focused in smoking products. Health misinformation about vaccines was also very common (43%), but studies reported different levels of misinformation depending on the different vaccines, with the Human Papilloma Virus (HPV) vaccine being the most affected. Secondly, health misinformation related to diets or pro eating disorders (pro-ED) arguments were moderate in comparison to the aforementioned topics (36%). Studies focused on diseases (i.e. non-communicable diseases and pandemics) also reported moderate misinformation rates (40%), especially in the case of cancer. Finally, the lowest levels of health misinformation were related to medical treatments (30%).
Conclusions: Prevalence of health misinformation was most common on Twitter and on issues related to smoking products and drugs. However, misinformation is also high on major public health issues such as vaccines and diseases. Our study offers a comprehensive characterization of the dominant health misinformation topics and a comprehensive description of their prevalence in different social media platforms, which can guide future studies and help in the development of evidence-based digital policy actions plans.

Keywords: social media; health misinformation; social networks; poor quality information; social contagion.

Introduction

Over the last two decades, internet users have increasingly used social media to seek and share health information [1]. These social platforms have gained wider participation among health information consumers from all social groups regardless of gender or age [2]. Health professionals and organizations are also using this medium to disseminate health-related knowledge on healthy habits and medical information for disease prevention as it represents an unprecedented opportunity to increase health literacy, self-efficacy, and treatment adherence among populations [3–9]. However, these public tools have also opened the door to unprecedented social and health risks [10,11]. Although these platforms have demonstrated usefulness for health promotion [7,12], recent studies suggest that false or misleading health information may spread more easily than scientific knowledge through social media [13,14]. Therefore, it is necessary to understand how health misinformation spreads and how it can affect decision-making and health behaviors [15].

Although the term ‘health misinformation’ is increasingly present in our societies, its definition is becoming increasingly elusive due to the inherent dynamism of social media ecosystem and the broad range of health topics [16]. Using a broad term that can include the wide variety of definitions in scientific literature, here we define health misinformation as a health-related claim that is currently based on anecdotal evidence, false, or misleading due to the lack of existing scientific knowledge [1]. This general definition would consider, on the one hand, information that is false, but not created with the intention of causing harm (i.e., misinformation) and, on the other, information that is false or based on reality, but deliberately created to harm a particular person, social group, institution or countries (i.e., disinformation and malinformation, respectively).

The fundamental role of health misinformation on social media has been recently highlighted by the Covid-19 pandemic, as well as the need of quality and veracity of health messages in order to manage the present public health crisis and the subsequent infodemic. In fact, in these days, the propagation of health misinformation through social media has become a major public health concern [17]. The lack of control over health information on social media is used as evidence for current demands to regulate the quality and public availability of online information [18]. In fact, although today there is broad agreement among health professionals and policy makers on the need to control health misinformation, there is still little evidence about the effects that the dissemination of false or misleading health messages through social media could have on public health in the near future. Although recent studies are exploring innovative ways to effectively combat health misinformation online [19–22], additional research is needed to characterize and capture this complex social phenomenon [23].

More specifically, four knowledge gaps have been detected from the field of public health [1]. Firstly, we have to identify the dominant health misinformation trends and specifically assess their prevalence on different social platforms. Secondly, we need to understand the interactive mechanisms and factors that make it possible to progressively spread health misinformation through social media (e.g. vaccination myths, miracle diets, alternative treatments based on anecdotal evidence, misleading advertisements on health products, among others). Factors such as the sources of misinformation, the structure and dynamics of online communities, the idiosyncrasies of social media channels, the motivations and profile of people seeking health information, the content and framing of health messages, or the context in which misinformation is shared are critical to understanding the dynamics of health misinformation through these platforms. For instance, although it is widely recognized the role of social bots in spreading misinformation through social media platforms during political campaigns and election periods, the health debates in social media are also affected by social bots [24]. Today, social bots are used to promote certain products in order to increase companies' profits, but also for the benefit of certain ideological positions or even against health evidence, such as in the case of vaccines [25].

Thirdly, a key challenge in epidemiology and public health research is to determine not only the effective impact of these tools in the dissemination of health misinformation, but also their impact on the development and reproduction of unhealthy or dangerous behaviors. Finally, regarding health interventions, we need to know which strategies are best in fighting and reducing the negative impact of health misinformation without reducing the inherent communicative potential to propagate health information with these same tools.

In line with the above mentioned gaps, a recent work represents one of the first steps forward in the comparative study of health misinformation in social media [16]. Through a systematic review of the literature, this study offers a general characterization of the main topics, areas of research, methods and techniques used for the study of health misinformation. However, despite the commendable effort made to compose a comprehensible image of this highly complex phenomenon, the lack of objective indicators that make it possible to measure the problem of health misinformation is still evident today.

Taking into account this wide set of considerations, this systematic review aims to specifically address this knowledge gap. In order to guide future studies in this field of knowledge, our objective is to identify and compare the prevalence of health misinformation topics on social media platforms, paying specific attention to the methodological quality of the studies and the diverse analytical techniques that are being implemented to address this public health concern.

Methods

This systematic review was conducted according to the Preferred Reporting Items for Systematic reviews and Meta-Analyses guidelines [26].

Inclusion Criteria

Studies were included if: (1) the objectives of the research were to: a) address the study of health misinformation on social media, b) search systematically for health misinformation, c) explicitly discuss the impact, consequences or purposes of misinformation; (2) the results of the studies: a) were based on empirical results, b) using quantitative, qualitative and also computational methods; and (3) studies were specifically focused on social media platforms (e.g. Twitter, Facebook, Instagram, Flickr, Sina Weibo, VK, YouTube, Reddit, Myspace, Pinterest and WhatsApp). For comparability, we included studies written in English that were published after 2000 until March 2019.

Exclusion Criteria

Articles were excluded if they addressed health information quality in general or if they partially mentioned the existence of health misinformation without providing empirical findings. We did not include studies that dealt with content posted on other social media platforms. During the screening process, papers with a lack of methodological quality were also excluded.

Search Strategy

We searched MEDLINE and PREMEDLINE in March 2019 using the PubMed search engine. Based on previous findings [16], the query searched for MeSH terms and keywords–in the entire body of the manuscript–related to three basic analytical dimensions that articulated our research objective: 1) Social media, 2) Health, and 3) Misinformation. The MeSH terms were: Social media AND Health (i.e., this term included health behaviors) AND (Misinformation OR Information seeking behavior OR Communication OR Health knowledge, attitudes, practice). Based on the results found through this initial search, we additionally added some keywords that (having been extracted from the articles that met the inclusion criteria) were specifically focused on the issue of health misinformation in social media. The search using MeSH terms was supplemented with the following keywords: Social Media (e.g., 'twitter' OR 'facebook' OR 'instagram' OR 'flickr' OR 'sina weibo' OR 'youtube' OR 'pinterest') AND Health AND Misinformation (e.g., 'inaccurate information' OR 'poor quality information' OR 'misleading information' OR 'seeking information' OR 'rumor' OR 'gossip' OR 'hoax' OR 'urban legend' OR 'myth' OR 'fallacy' OR 'conspiracy theories'). This initial search retrieved 1693 records. Additionally, this search strategy was adapted for its use in SCOPUS (3969 records) and Web of Science (1541 records). A full description of the search terms can be found in table 1A of supplementary files.

Study Selection

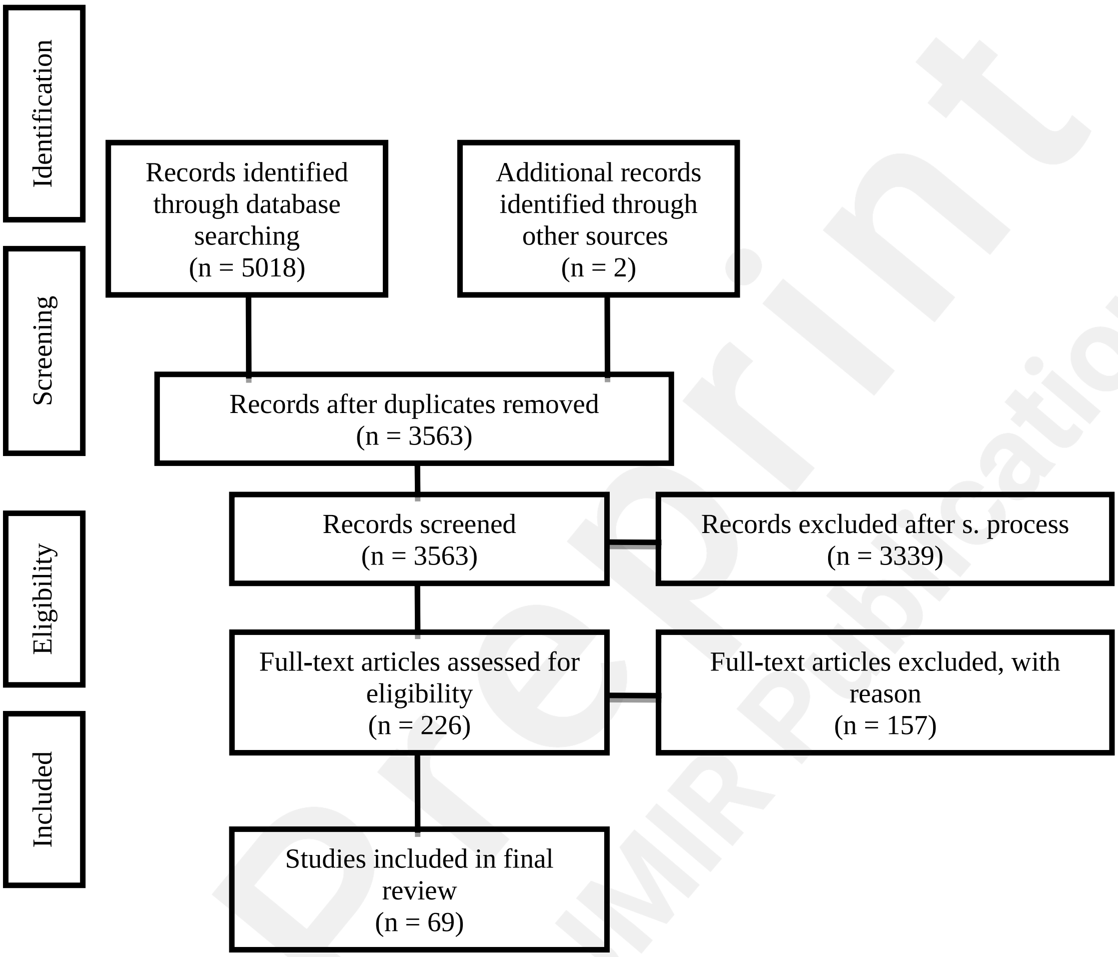
In total, we collected 5018 research articles. After removing duplicates, we screened 3563 and retrieved 226 potentially eligible articles. In the next stage, the authors independently carried out a full-text selection process for inclusion (k = .89). Discrepancies were shared and resolved by mutual agreement. Finally, a total of 69 articles were included in this systematic review (figure 1).

Data extraction

In the first phase, the data were extracted by (anonymized) and then checked by (anonymized) and (anonymized). In order to evaluate the quality of the selected studies and given the wide variety of methodologies and approaches found in the articles, we composed an extraction form based on previous works. Each extraction form contained 62 items, most of which were closed questions that could be answered using predefined forms (Yes/Good, No/Poor, Partially/Fair, ...). Following this coding scheme, we extracted 4 different fields of information: a) descriptive information (27 items), b) search strategy evaluation (8 items), c) information evaluation (6 items) and d) the quality and rigor of methodology and reporting (15 items) for either quantitative or qualitative studies (see Table 1A in supplementary files). Questions in field b), used in previous studies [27], assessed the quality of information provided to demonstrate how well-reported, systematic and comprehensive the search strategy was (S-Score). The items in field c) measured how rigorous the evaluation was (E-Score) for health-related misinformation [27]. Field d) contained items designed for the general evaluation of quality in the research process whether quantitative [28] or qualitative [29]. This Q-Score approach takes into account general aspects of the research and reporting, such as the study, the methodology or quality of discussion, among other aspects. For each of the information fields, we calculate the raw score as the sum of each of the items by equating 'Yes' or 'Good' as 1 point, 'Fair' as 0.5 points, and 'No' or 'Poor' as 0 points (see table 2A in supplementary files for more information). The purpose of these questions is to guarantee the quality of the selected studies.

Furthermore, in order to be able to compare the methods used in the selected studies, the authors classified the works into several categories. The studies classified as 'Content / Text Analysis' used methods related to textual and content analysis, emphasizing the word/topic frequency, Linguistic Inquiry Word Count (LIWC), n-grams, etc. Secondly, the category 'Evaluating Content' groups together studies whose methods were focused on the evaluation of content and information. In general, these studies analyzed different dimensions of the information published on social media. Third, 'Evaluating Quality', these studies analyzed the quality of the information offered in a global way. This category considered other dimensions in addition to content such as readability, accuracy, usefulness, and sources of information. The fourth category, 'Sentiment Analysis', included studies whose methods were focused on sentiment analysis techniques, i.e. methods measuring the reactions and the general tone of the conversation on social media. Finally, the 'Social Network Analysis' category included those works whose methods were based on social network analysis techniques. These studies focused on measuring how misinformation spreads in social media, the relationship between the quality of information and its popularity in these social platforms, the relationship between users and opinions, echo-chambers effects and opinion formation.

Figure 1 Preferred Reporting Items for Systematic Reviews and Meta-Analyses flow chart.



Of the 226 studies available for full-text review, 157 were excluded for various reasons including research topics which were not focused on health misinformation (133). We also excluded: articles whose research was based on websites rather than social media platforms (16), studies that did not assess the quality of health information (6) or evaluated institutional communications (5), non-empirical studies (2) and research protocols (1). In addition, two papers were excluded because of the lack of quality requirements (Q-Score < 50%). Finally, the protocol of this review was registered at the international prospective register of systematic reviews PROSPERO (CRD42019136694).

Results

Ultimately, 69 studies were identified as eligible, covering a wide range of health topics and social media platforms including Twitter as the most common data source (43%, 29/69), YouTube (37%, 25/69), Facebook (9%, 6/69) and to a lesser extent Instagram, MySpace, Pinterest, Tumblr, WhatsApp and VK or a combination of the above. A 90% (61/69), were published in health science journals. Just a 7% of the articles (5/69) were published in communication journals. The vast majority of articles analyzed posts written exclusively in one language (91%, 63/69). Only a small percentage assessed posts in more than one language (10%, 6/69).

Table 1 classifies the studies by topic and social media platform. It also includes the prevalence of health misinformation (PHM) posts. As we can observe the topics were articulated around six principal categories: vaccines (32%), drugs or smoking issues (22%), non-communicable disease (19%), pandemics (10%), eating disorders (9%), and medical treatments (7%). The quality assessment results for S-Score, E-Score, and Q-Score are reported in table 3A of supplementary files.

Table 1. Summary of prevalence of misinformation by topic and social media platform.

Authors	Year	Topic	Social Media Platform	PHM posts
Abukaraky et al. [30]	2018	Treatment	YouTube	30%
Ahmed et al. [31]	2019	Pandemic	Twitter	NA
Al Khaja et al. [32]	2018	Drugs	WhatsApp	27%
Allem et al. [33]	2017	Drugs	Twitter	59%
Allem et al. [34]	2017	Drugs	Twitter	NA
Arseniev-Koehler et al. [35]	2016	ED	Twitter	36%
Basch et al. [36]	2017	Vaccine	YouTube	65%
Becker et al. [37]	2016	Vaccine	Twitter	1%
Biggs et al. [38]	2013	NCD	YouTube	39%
Blankenship et al. [39]	2018	Vaccine	Twitter	24%
Bora et al. [40]	2018	Pandemic	YouTube	23%
Branley et al. [41]	2017	ED	Twitter & Tumblr	25%
Briones et al. [42]	2012	Vaccine	YouTube	51%
Broniatowski et al. [23]	2018	Vaccine	Twitter	35%
Buchanan et al. [43]	2014	Vaccine	Facebook	43%
Butler et al. [44]	2013	Treatment	YouTube	NA
Cavazos-Rehg et al. [45]	2018	Drugs	Twitter	75%
Chary et al. [46]	2017	Drugs	Twitter	0%
Chew et al. [47]	2010	Pandemic	Twitter	4%
Covolo et al. [48]	2017	Vaccine	YouTube	23%
Dunn et al. [49]	2015	Vaccine	Twitter	25%
Dunn et al. [50]	2017	Vaccine	Twitter	NA

Ekram et al. [51]	2018	Vaccine	YouTube	57
Erdem et al. [52]	2018	Treatment	YouTube	0%
Faasse et al. [53]	2016	Vaccine	Facebook	NA
Fullwood et al. [54]	2016	Drugs	YouTube	34%
Garg et al. [55]	2015	Vaccine	YouTube	11%
Gimenez-Perez et al. [56]	2018	NCD	YouTube	50%
Goobie et al. [57]	2019	NCD	YouTube	NA
Guidry et al. [58]	2017	Pandemic	Twitter & Instagram	NA
Guidry et al. [59]	2016	Drugs	Pinterest	97%
Guidry et al. [60]	2015	Vaccine	Pinterest	74%
Hanson et al. [61]	2013	Drugs	Twitter	0%
Harris et al. [62]	2018	ED	Twitter	NA
Haymes et al. [63]	2016	NCD	YouTube	47%
Helmi et al. [64]	2018	NCD	Dif. sources	NA
Kang et al. [65]	2017	Vaccine	Twitter	42%
Katsuki et al. [66]	2015	Drugs	Twitter	6%
Keelan et al. [67]	2010	Vaccine	MySpace	43%
Keim-Malpass et al. [68]	2017	Vaccine	Twitter	43%
Kim et al. [69]	2017	NCD	YouTube	22%
Krauss et al. [70]	2017	Drug	Twitter	50%
Krauss et al. [71]	2015	Drug	Twitter	87%
Kumar et al. [72]	2014	NCD	YouTube	33%
Laestadius et al. [73]	2016	Drugs	Instagram	NA
Leong et al. [74]	2018	NCD	YouTube	33%
Lewis et al. [75]	2015	Treatment	YouTube	NA
Loeb et al. [76]	2018	NCD	YouTube	77%
Love et al. [77]	2013	Vaccine	Twitter	13%
Martinez et al. [78]	2018	Drugs	Twitter	67%
Massey et al. [79]	2016	Vaccine	Twitter	25%
McNeil et al. [80]	2012	NCD	Twitter	41%
Menon et al. [81]	2017	Treatment	YouTube	2%
Merianos et al. [82]	2016	Drugs	YouTube	65%

Meylakhs et al. [83]	2014	NCD	VK	NA
Morin et al. [84]	2018	Pandemic	Twitter	NA
Mueller et al. [85]	2019	NCD	YouTube	66%
Porat et al. [86]	2019	Pandemic	Twitter	0%
Radzikowski et al. [87]	2016	Vaccine	Twitter	NA
Schmidt et al. [88]	2018	Vaccine	Facebook	4%
Seltzer et al. [89]	2017	Pandemic	Instagram	60%
Seymour et al. [90]	2015	NCD	Facebook	NA
Syed-Abdul et al. [91]	2013	ED	YouTube	29%
Teufel et al. [92]	2013	ED	Facebook	22%
Tiggermann et al. [93]	2018	ED	Twitter	29%
Tuells et al. [94]	2015	Vaccine	YouTube	12%
van der Tempel et al. [95]	2016	Drugs	Twitter	NA
Waszak et al. [96]	2018	NCD	Facebook	40%
Yang et al. [97]	2018	Drugs	YouTube	98%

Figure 2 shows the prevalence of health misinformation grouped by different topics and social media typology. Studies are ordered according to the percentage of health misinformation posts found in the studies selected. These works were also classified according to the type of social media under study. In this way, the papers focused on Twitter, Tumblr or Myspace were categorized as 'Microblogging'. Secondly, papers focused on YouTube, Pinterest or Instagram were classified within 'Media sharing' platforms. And third, Facebook, VK or WhatsApp were included within the group of 'Social Network' platforms. While all the topics were present on all the different social media platforms, we found some differences in their prevalence. On the one hand, vaccines, drugs or pandemics were more prevalent topics in microblogging platforms (i.e. Twitter or MySpace). On the other hand, in media sharing platforms (i.e. YouTube, Instagram or Pinterest) and social networks platforms (i.e. Facebook, VK or WhatsApp), non-communicable diseases (NCDs) and treatments were the most prevalent topics. More specifically, Twitter was the most used source for work on vaccines (10/69), drugs or smoking products (10/69), pandemics (4/69) and eating disorders (3/69). For studies on NCDs (9/69) or on treatments (5/69) YouTube was the most used social media.

Overall, health misinformation was most prevalent in studies related to smoking products such as hookah or water pipes[33,59,71], e-cigarettes, and drugs such as opioids or marijuana [45,70,97]. Health misinformation about vaccines was also very common. However, the studies reported different levels of health misinformation depending on the type of vaccine studied, with HPV being the most affected [67,68]. Health misinformation related to diets or pro-ED arguments were moderate in comparison to aforementioned topics [35,93]. Studies focused on diseases (i.e. NCDs and pandemics) also reported moderate misinformation rates [56,85], especially in the case of cancer [76,96]. Finally, the lowest levels of health misinformation were observed in studies evaluating the presence of health misinformation regarding medical treatments. Although the first-aid information on burns or information on dental implants was limited in quantity and quality, the prevalence of misinformation for these topics was low. Surgical treatment misinformation was the least prevalent. This was due to the fact that the content related to surgical treatments came from official accounts mainly, which made the online information more complete and reliable.

Regarding the methods used in the different studies, there were also some differences between the diverse social media platforms. We classified the studies based on the methods applied into five categories: Social Network Analysis (19/69), Evaluating Content (18/69), Evaluating Quality (16/69), Content/Text analysis (12/69) and Sentiment Analysis (4/69). Figure 3 shows the different methods applied in the studies classified by the type of social media platform and ordered by the percentage of misinformation post. Among platforms such as YouTube or Instagram, methods focused on the evaluation of health information quality and content were common, representing 22% (15/69) and 12% (8/69) respectively. While on microblogging platforms, such as Twitter or Tumblr, social network analysis was the method most used by 19% (13/69) of the studies. Finally, on social media platforms such as Facebook, VK or WhatsApp, studies whose methods were related to social network analysis represented a 3% (2/69) and those focused on the evaluation of content a 4% (3/69) .

Figure 2.Prevalence of health misinformation grouped by different topics and social media typology.

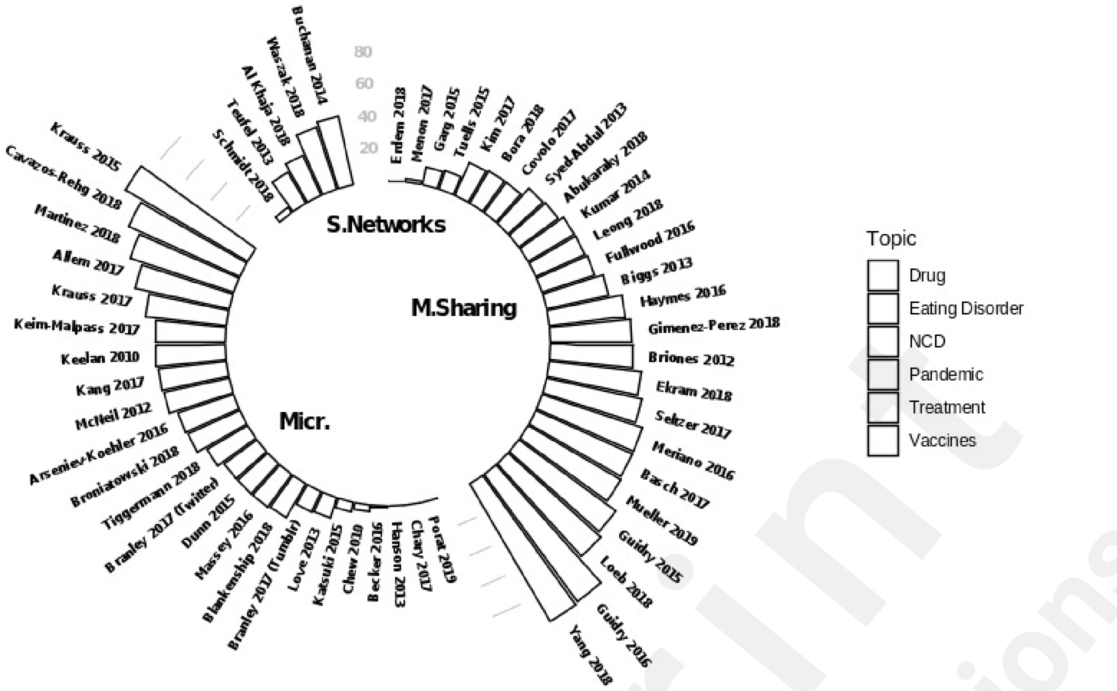
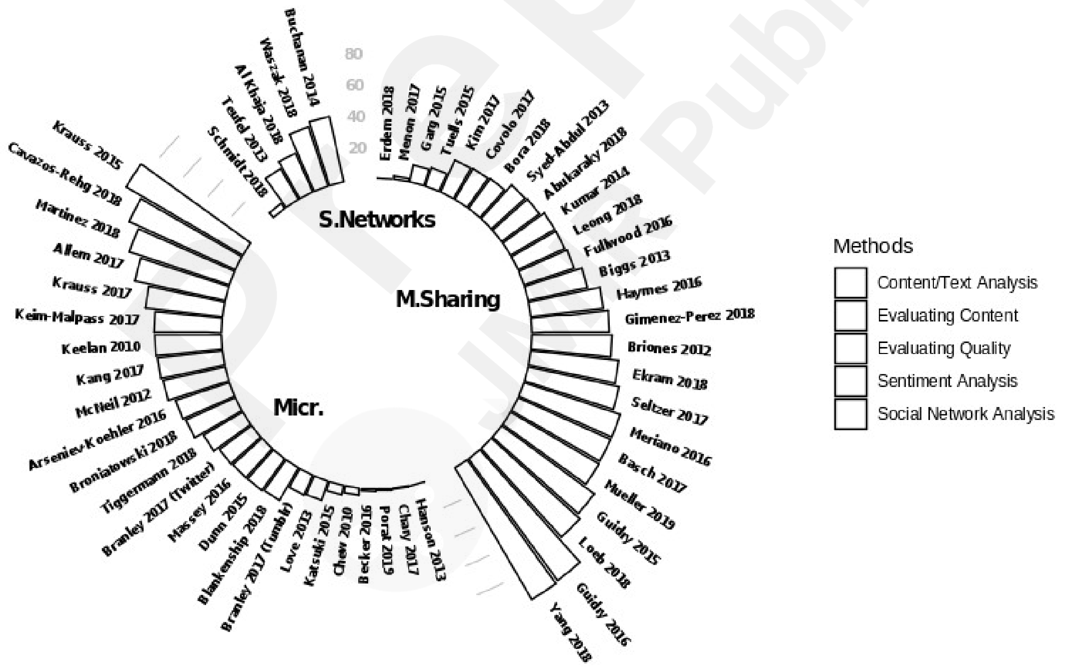


Figure 3. Percentage of health misinformation grouped by method and social media typology.



Misinformation topics and methods

Vaccines

Around 32% (22/69) of the studies focused on vaccines or vaccination decision-making related topics. A 14% (10/69) of selected articles focused on social media discussion regarding the potential side effects of vaccination [23,36,48,53,55,60,65,77,87,88], a 12% (8/69) were centered on the debate around the Human Papilloma Virus (HPV) vaccine [42,49–51,67,68,79,94], and a 3% (2/69) on the anti-vaccine movement [39,43]. By social media platforms, a 9% (6/69) of the studies were focused on the debate and narratives about vaccines in general on Twitter, and a 6% (4/69) specifically analyzed the HPV debate on this platform. Papers focused on YouTube also follow a similar trend being centered on the HPV debate and on the public discussion on vaccines side effects and risks for specific population groups (e.g. autism in children). In Facebook all the works were particularly focused on vaccination decision-making.

Most authors studied differences in language use; the effect of heterogeneous community structure in the propagation of health misinformation; and the role played by fake profiles or bots in the spread of poor quality, doubtful or ambiguous health content. In line with these concerns, the authors pointed out the need to further study the circumstances surrounding those who adopt these arguments [49], and whether alternative strategies to education could improve the fight against anti-vaccine content [51]. Authors also recommended paying close attention to social media as these tools are assumed to play a fundamental role in the propagation of misinformation. For instance, the role played by the echo-chambers or the heterogeneous community structure on Twitter has demonstrated to skew the information to which users are exposed in relation to HPV vaccines [49]. In this sense, it is widely acknowledged that health professionals should pay more attention to anti-vaccine arguments in social media, so that they can better respond to patients' concerns [36,43,65,77]. Furthermore, governmental organizations could also use social media platforms to reach a greater number of people [39,55].

Drugs and Smoking

Several studies (22%, 15/69) covered misuse and misinformation about e-cigs, marijuana, opioid consumption, and prescription drug abuse. Studies covering the promotion of e-cigs use and other forms of smoking such as hookah (i.e. water pipes or narghiles) represented a 7% (4/69) of the articles analyzed. The rest (16%, 11/69) were focused on the analysis of drug misinformation.

By topics, regarding drug and opioid use, the papers investigated the dissemination of misinformation through social media platforms [32,45,46,70,97]; the relationship between the consumption of misinformation related to these products; the drug abuse and the sale of online medical products [61,66]. These studies highlighted the risk, especially for young people, caused by the high rate of misinformation related to the dissemination of drug practice and misuse (predominantly marijuana and opioids) [45]. In addition, social media platforms were identified as a potential source of illegal promotion of the sale of controlled substances directly to consumers [66]. Most drug-related messages on social media were potentially misleading or false claims that lacked credible evidence to support them [32]. Other studies pointed to social media as a potential source of information that illegally promotes the sale of controlled prescription drugs directly to consumers [66]. In the case of cannabinoids, there was often content that described, encouraged, promoted the use [54] or even normalized the consumption of illicit substances [70].

Unlike drug studies, most of the papers analyzed how e-cigs and hookah [33,34,59,71,73,78,82,95] are portrayed in social media and/or the role of bots in promoting e-cigs. Regarding e-cigs, studies pointed out the high prevalence of misinformation denying health damage [95]. In this sense, it is worth noting the importance of sources of misinformation. While in the case of vaccines, the source of health misinformation were mainly individuals or groups of people with a particular interest (e.g. anti-vaccine movement), social media was found to be frequently contaminated by the misinformation of bots, i.e. software applications that autonomously run tasks such as spreading positive discourse about e-cigs and other tobacco products [78]. In fact, these fake accounts may influence the online conversation in favor of e-cigs given the scientific appearance of profiles [78]. Some of the claims found in this study denied the harmfulness of e-cigs. In line with these findings, other studies pointed to the high percentage of messages favoring electronic cigarettes as an aid to quitting smoking [95].

We found that 10% (7/69) of the studies used methods focused on evaluating the content of the posts. These works aimed to explore the misperceptions of drugs abuse or alternative forms of tobacco consumption. Along these lines, another study focused on evaluating the quality of the content (1%, 1/69). The authors evaluated the truthfulness of claims about drugs. In particular, we found that 7% (5/69) of the studies used social network analysis techniques. These studies analyzed the popularity of the messages based on whether they promoted illegal access to drugs online and the interaction of users with this content. Other studies used content analysis techniques (3%, 3/69). These studies evaluated the prevalence of misinformation on platforms and geographically, as a kind of 'toxicosurveillance' system [34,46].

Non-communicable diseases

A relevant part of studies assessed non-communicable diseases (NCD) (19%, 13/69) such as cancer, diabetes, epilepsy, among others. Most of the studies focused on the objective evaluation of information quality on YouTube [38,56,57,69,72,74,76,80,85]. A 13% (9/69) of these works used methods to assess the quality of the information. The authors analyzed the usefulness and accuracy of the information. Second, 4% (3/69) of the studies used methods related to content assessment. The main objective of these studies was to analyze which are the most common misinformation topics. A 3% (2/69) used social network analysis and the main objective of the analyzes was to study the information dissemination patterns or the social spread of scientifically inaccurate health information.

Some studies evaluated the potential of this platform as a source of information specially for health students or self-directed education among the general public. Unfortunately, the general tone of research findings was that YouTube is not an advisable source for health professionals, nor for health information seekers. Regarding diabetes, the probability of finding misleading videos was high [56]. Misleading videos promoted cures for diabetes, negated scientific arguments, or provided treatments with no scientific basis. Furthermore, misleading videos related to diabetes were found to be more popular than those with evidence-based health information [74] which increased the probability of consuming low-quality health contents. The same misinformation pattern was detected with other chronic diseases such as hypertension [72], prostate cancer [76] and epilepsy [80].

Pandemic and communicable diseases

Results indicated that 10% of the studies (7/69) covered misinformation related to pandemics and communicable diseases such as H1N1 Virus [31,47], Zika [40,89], Ebola [58,84] or diphtheria [86]. All these works analyzed how online platforms were used by both health information seekers and health and governmental authorities during the pandemic period.

We found that 14% of the studies (10/69) on this topic evaluated the quality of the information. To achieve this, most of these studies used external instruments such as DISCERN and AAD7 Self-Care Behaviors. A 9% (6/69) of the papers evaluated the content of the information. These studies were focused on the analysis of the issues of misinformation. Another 4% (3/69) used social media analysis to observe the propagation of misinformation. Finally, a 3% (2/69) used textual analysis as the main method. These studies focused on the study of the prevalence of health misinformation.

These studies identified social media as a public forum for free discussion, but also indicated that this freedom might lead to rumors on anecdotal evidence and misunderstandings regarding pandemics. Consequently, although social media was described as a forum for sharing health-related knowledge, these tools are also recognized by researchers and health professionals as a source of misinformation that needs to be controlled by health experts [83,84]. Therefore, while social media serves as a place where people commonly share their experiences and concerns, these platforms can be potentially used by health professionals to fight against false beliefs on communicable diseases (e.g. as it is happening today during the Covid-19 pandemic). Accordingly, social media platforms have been found to be a powerful tool for health promotion among governmental institutions and health-related workers, an new instrument that, for instance, is being used to increase health surveillance and intervention against false beliefs and misinformation nowadays [31,89]. In fact, different authors agreed that governmental/health institutions should increase their presence on social media platforms during pandemic crises [47,58,84,86].

Diet/Eating Disorders

Papers focused on diet and eating disorders (ED) represented a 9% (6/69). This set of studies identified pro-ED groups and discourses within social media [35], and how pro-ED information was shared and spread on these platforms [91]. Anorexia was the most studied ED along with bulimia. Furthermore, discourses promoting fitness or recovery after an ED were often compared with those issued by pro-ED groups [41,62,92,93]. In general, the authors agreed on the significance of pro-ED online groups, the mutual support among members and the way they reinforce their opinions and health behaviors [35].

First, a 4% (3/69) of studies used social network analysis techniques. The authors focused on analyzing the existing connections between individuals in the pro-ED community and their engagement, or comparing the cohesion of these communities with other communities such as the fitness community that promote healthier habits. Second, a 3% (2/69) evaluated the quality of the content and particularly focusing on the informative analysis of the videos. That is, the content was classified as informative if it described the health consequences of anorexia; or pro-ana if, on the contrary, anorexia was presented as a fashion, or a source of beauty. Third, only one study used content analysis techniques. The authors classified the posts according to the following categories: pro-ana, anti-ana and pro-recovery. Pro-ED pages tended to identify themselves with body-associated pictures due to the importance they attributed to motivational aspects of pro-ED communities [92]. The pro-ED claims contained practices about weight loss, wanting a certain body type or characteristic of a body part, eating disorders, binge eating, and purging [62]. Pro-ED conversations also have a high content of social support in the form of tips and tricks (e.g., “Crunch on some ice chips if you are feeling a hunger craving. This will help you feel as if you are eating something substantial”, “How do you all feel about laxatives?”) [92].

Regarding ED on social media, paying attention to community structure was also important according to the authors. Although it is widely acknowledged that communities can be positive by providing social support such as recovery or well-being, certain groups in social media may also reaffirm pro-ED identity [35]. In fact, polarized pro/anti-ED communities can become closed echo-chambers where community members are selectively exposed to the content they are looking for and therefore only hear the arguments they want to hear. In this case, the echo chamber effect might explain why information campaigns are limited in scope and often encourage polarization of opinion and can even reinforce existing divides in pro-ED opinions [88].

Treatment and medical interventions

Finally, we found that 7% (5/69) of studies assessed the quality of health information regarding different medical treatments or therapies recommended through social media [63,81]. By method, a 6% (4/69) of the studies evaluated the quality of the information related to the proposed treatments and therapies. In this sense, the fundamental goal of these works was aimed to study the quality and accuracy of the information.

As in the case of NCDs, professionals scanned social networks, (especially YouTube) evaluating the quality of online health content as an adequate instrument for self-care or for health students' training. There were specific cases where information was particularly limited in quality and quantity such as dental implants, or first-aid information on burns [30,44]. However, most surgical treatments or utensils were found to have a sufficient level of quality information on YouTube [52,81]. In relation to this topic it is worthy to point out the source of the misinformation. In this particular case, most of the posts were published by private companies. They used the platforms to promote their medical products. Therefore, the amount of misinformation was significantly low compared with other topics such as ED or vaccines that are closely linked to the general public. In general, the videos were accurate, well presented, and framed treatments in a useful way for both health workers and health information seekers.

A full description of the objectives and main conclusions of the reviewed articles can be found in table 4A of supplementary files.

Discussion

Main findings

This work represents, to our knowledge, the first effort aimed at finding objective and comparable measures to quantify the extent of health misinformation in the social media ecosystem. Our study offers an initial characterization of the dominant health misinformation topics and specifically assesses their prevalence on different social platforms. Therefore, our systematic review provides new insights on an unanswered question that has been recurrently highlighted in studies of health misinformation in social media: How prevalent is health misinformation for different topics on different social platform types (i.e. micro-blogging, media sharing, and social networks)?

We have found that health misinformation in social media is generally linked to six topical domains: (1) vaccines; (2) diets and eating disorders; (3) drugs and new tobacco products; (4) pandemic and communicable diseases; (5) NCDs; and (6) medical treatments and health interventions.

With regard to vaccines, we have found some interesting findings throughout the different studies. Although anti-vaccine ideas have been traditionally linked to emotional discourses against the rationality of scientific and expert community, we have curiously observed that in certain online discussions, anti-vaccine groups also tend to incorporate scientific language in their own discourse by using logically structured statements and/or with less usage of emotional expressions [53]. Thus, the assimilation of the scientific presentation and its combination with anecdotal evidence can rapidly spread along these platforms through a progressive increment of visits and 'likes' that can make anti-vaccine arguments particularly convincing for health information seekers [53,55]. Furthermore, we have found that the complex and heterogeneous community structure of these online groups must be taken into account. For instance, those more exposed to anti-vaccine information tend to spread more negative concerns about vaccines (i.e. misinformation or opinions related to vaccine hesitancy) than users exposed to positive or neutral opinions [49]. Therefore, negative/positive opinions are reinforced through the network structure of particular social media platforms. Moreover, fake profiles tend to amplify the debate and discussion, thereby undermining the possible public consensus on the effectiveness and safety of vaccines, especially in the case of Human Papilloma Virus (HPV), Measles, Mumps and Rubella (MMR), and influenza [23].

As observed in our review, the health topics were omnipresent over all social media platforms included in our study, however, the health misinformation prevalence for each topic varies depending on platform characteristics. Therefore, the potential effect on population health is ambivalent, i.e. we found both positive and negative depending on the topic and on the group of health information seekers. For instance, content related to eating disorders was frequently hidden, or is at least not so evident to the general public, since pro-ED communities use their own codes to reach specific audiences (e.g. younger groups) [98]. To provide a simple example, it is worth mentioning the usage of nicknames such as pro-ana or pro-mia, respectively for pro-anorexia and pro-bulimia, as a way to reach people with these health conditions and make it easier for people to talk openly about their eating disorders. More positively, these tools have also proved useful in prevention campaigns during health crises. For example, during H1N1, Ebola or Zika pandemics (and, even more recently, with the ongoing Covid-19 pandemic), platforms such as Twitter were valuable instruments for spreading evidence-based health knowledge, expert recommendations, and educative content aimed at avoiding the propagation of rumors, risk behaviors, and diseases [31,89].

Throughout our review, we found different types of misinformation claims depending on the topics. Concerning vaccines, misinformation was often framed with a scientific appearance against scientific evidence [53]. Drug-related misinformation promoted the consumption and abuse of these substances [66]. However, these statements lacked scientific evidence to support them [32]. As with vaccines, the false accounts that influenced the online conversation did so with a scientific appearance in favor of electronic cigarettes [82]. In this sense, most accounts tended to promote the use and abuse of these items. Having beauty as a final goal, misinformation about eating disorders promoted changes in the eating habits of social media users [91]. Furthermore, we found that social media facilitated the development of pro-ED online communities [35]. In general, the results indicated that this type of content promoted unhealthy practices while normalizing eating disorders. In contrast, epidemics/pandemics related misinformation was not directly malicious. Misinformation on this topic was made up of rumors, misunderstandings, or doubts arising from a lack of scientific knowledge [31]. These statements were within the framework of the health emergency arising from the pandemic. In line with these findings were also those related to non-communicable diseases. Messages that focused on this topic promoted cures for chronic diseases or for which was no cure through fallacies or urban legends [85].

Although in this study we have focused on the analysis of the results obtained and the conclusions of the authors. Some of our findings are in line with those obtained in recent works [16].The reviewed studies indicate: on the one hand, the difficulty in characterizing and evaluating the quality of health information on social media [1]; and on the other, the conceptual fuzziness that can result due to the convergence of multiple disciplines trying to apprehend the multidisciplinary and complex phenomenon of health misinformation in social media. This research field is being studied by health and social scientists [70,73], but also by researchers from the fields of computer science, math, and sociophysics, among others [99,100]. Therefore, we must understand that the inherent multidisciplinary and methodological diversity of studies and the highly dynamic world of social media are a perfect match to make more difficult to identify comprehensive and transversal solutions to the problem of health misinformation. In fact, as we have found, misinformation on vaccines, drugs and new smoking products are more prevalent in media-sharing platforms (e.g. YouTube) and micro-blogging applications (e.g. Twitter), while misinformation on NCDs is particularly prevalent in media sharing platforms where users can widely describe disease symptoms, medical treatments and therapies [76,85]. That is, platforms such as YouTube, due to their characteristics, allow more space for users to share this type of information, while the natural dynamism of Twitter makes it an ideal medium for discussion among online communities with different political or ideological orientation (e.g., pro/anti-vax communities).

Finally, we should mention that current results are also limited to the availability and quality of social media data. Although the digitalization of social life offers researchers an unprecedented amount of health and social information that can be used to understand human behaviors and health outcomes, accessing this online data is becoming increasingly difficult and some measures have to be taken to mitigate bias [40,43,67,79]. Over the last few years, new concerns around privacy have emerged and led governments to tighten regulations around data access and storage [101,102]. Consequently, in response to these new directives, as well as scandals involving data sharing and data breaches such as the Cambridge Analytica case, social media companies are developing new controls and barriers to data in their platforms. This is the reason why free access to application programming interfaces (APIs) is becoming increasingly difficult and the range of social data accessible via APIs is gradually decreasing. These difficulties in accessing data are also determining which platforms are most frequently used by researchers, which are not, and which will be in the near future.

Limitations and strengths

Firstly, one of the limitations of this article lies on the conceptual definition of health misinformation. In any case, taking into account that we were facing a new field of study, we considered a broad definition in order to be more inclusive and operative in the selection of studies. Therefore, we managed to include as many papers as possible for the review so that we could perform an analysis of the largest number of possible topics. Secondly, from a methodological perspective, our findings are limited to research published in English language journals and not all the social media platforms that exist. Besides, we discovered some technical limitations when conducting this systematic review. Due to the newness of this research topic, our study revealed difficulties in comparing different research studies characterized by specific theoretical approaches, working definitions, distinct methodologies, data collection processes, and analytical techniques. Some studies selected were implemented through observational designs (using survey methods and textual analysis), while others were based on the application of automatic or semi-automatic computational procedures with the aim of classifying and analyzing health misinformation in social media. Finally, taking into account the particular features of each social media (i.e. microblogging services, video sharing, or social networks) and the progressive barriers in accessing social media data, we need to consider the information and selection bias when studying health misinformation in these platforms. According to these biases, we should ponder which users are behind these tools and how we can extrapolate specific findings (i.e. applied to certain groups and social media platforms) to a broader social context.

Despite the limitations described above, it is also necessary to mention the strengths of our work. First, we believe that this study represents one of the first steps in advancing research on health misinformation in social media. Unlike previous work, we offer some measures that can serve as guidance and a comparative baseline for subsequent studies. In addition, it highlights the need to redirect future research towards social media platforms which, perhaps due to the difficulties of automatic data collection, are currently being neglected by researchers. Our study also highlights the need for both researchers and health professionals to explore the possibilities of these digital tools for health promotion, and the need for them to progressively colonize the social media ecosystem with the ultimate goal of combating the waves of health misinformation that recurrently flood our societies.

Conclusion

Prevalence of health misinformation was most common on Twitter and on issues related to smoking products and drugs. Although we should be aware of the difficulties inherent in the dynamic magnitude of online opinion flows, our systematic review offers a comprehensive comparative framework that identifies subsequent action areas in the study of health misinformation in social media. Despite the above-mentioned limitations, our research work presents some advances when compared to previous studies. Our study provides: (1) an overview of the prevalence of health misinformation identified in different social media platforms; (2) a methodological characterization of studies focused on health misinformation; and (3) a comprehensive description of the current research lines and knowledge gaps in this research field.

According to the studies reviewed, the greatest challenge lies in the difficulty of characterizing and evaluating the quality of the information on social media. Knowing the prevalence of health misinformation and the methods used for its study, as well as the present knowledge gaps in this field will help us to guide future studies and, specifically, to develop evidence-based digital policy actions plans aimed to combat this public health problem through the different social media platforms.

Conflict of interest

The authors declare that they have no competing interests.

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References

1. Chou W, Oh A, WP K. Addressing health-related misinformation on social media. JAMA 2018 Nov 14; [doi: 10.1001/jama.2018.16865]
2. Xiong F, Liu Y. Opinion formation on social media: an empirical approach. Chaos 2014;24(1):013130. [doi: 10.1063/1.4866011]
3. Altevogt BM, Stroud C, Hanson SL, Hanfling D, Gostin LO E. Guidance for Establishing Crisis Standards of Care for Use in Disaster Situations. Guid Establ Cris Stand Care Use Disaster Situations. 2009. [doi: 10.17226/12749]
4. Funk S, Gilad E, Watkins C, Jansen VAA. The spread of awareness and its impact on epidemic outbreaks. Proc Natl Acad Sci U S A 2009 Apr;106(16):6872–7. PMID:19332788
5. Funk S, Salathé M, Jansen VAAA. Modelling the influence of human behaviour on the spread of infectious diseases: A review. J R Soc Interface Sep, 2010 p. 1247–56. PMID:20504800
6. Kim SJ, Han JA, Lee T-YY, Hwang T-YY, Kwon K-SS, Park KS, Lee KJ, Kim MS, Lee SY. Community-based risk communication survey: Risk prevention behaviors in communities during the H1N1 crisis, 2010. Osong Public Heal Res Perspect 2014 Feb;5(1):9–19. PMID:24955307
7. Mcgloin AF, Eslami S. Digital and social media opportunities for dietary behaviour change. Proc Nutr Soc 2014. p. 139–148. PMID:25319345
8. Scarcella C, Antonelli L, Orizio G, Rossmann CC, Ziegler L, Meyer L, Garcia-Jimenez L,

Losada JC, Correia J, Soares J, Covolo L, Lirangi E, Gelatti U. Crisis communication in the area of risk management: the CriCoRM project. J Public health Res 2013 Sep;2(2):e20. PMID:25170491
9. Dredze M, Broniatowski DA, Smith MC, Hilyard KM. Understanding Vaccine Refusal: Why We Need Social Media Now. Am J Prev Med 2016; [doi: 10.1016/j.amepre.2015.10.002]
10. Cavallo DN, Chou WYS, Mcqueen A, Ramirez A, Riley WT. Cancer prevention and control interventions using social media: User-generated approaches. Cancer Epidemiol Biomarkers Prev 2014; [doi: 10.1158/1055-9965.EPI-14-0593]
11. Naslund JA, Grande SW, Aschbrenner KA, Elwyn G. Naturally occurring peer support through social media: The experiences of individuals with severe mental illness using you tube. PLoS One 2014; [doi: 10.1371/journal.pone.0110171]
12. Sama PR, Eapen ZJ, Weinfurt KP, Shah BR, Schulman KA. An Evaluation of Mobile Health Application Tools. JMIR mHealth uHealth 2014 May;2(2):e19. [doi: 10.2196/mhealth.3088]
13. Vosoughi S, Roy D, Aral S. The spread of true and false news online. Science (80-) 1200 NEW YORK AVE, NW, WASHINGTON, DC 20005 USA: AMER ASSOC ADVANCEMENT SCIENCE; 2018 Mar;359(6380):1146+. [doi: 10.1126/science.aap9559]
14. Levy JA, Strombeck R. Health benefits and risks of the internet. J Med Syst 2002;26(6):495–510. [doi: 10.1023/A:1020288508362]
15. Pagoto S, Waring ME, Xu R. A Call for a Public Health Agenda for Social Media Research. J Med Internet Res JMIR Publications; 2019 Dec 19;21(12):e16661–e16661. [doi: 10.2196/16661]
16. Wang Y, McKee M, Torbica A, Stuckler D. Systematic Literature Review on the Spread of Health-related Misinformation on Social Media. Soc Sci Med. 2019. PMID:31561111
17. Venkatraman A, Mukhija D, Kumar N, Nagpal SJS. Zika virus misinformation on the internet. Travel Med Infect Dis 2016; [doi: 10.1016/j.tmaid.2016.05.018]
18. Freeman B, Kelly B, Baur L, Chapman K, Chapman S, Gill T, King L. Digital junk: Food and beverage marketing on facebook. Am J Public Health 2014; [doi: 10.2105/AJPH.2014.302167]
19. Bode L, Vraga EK. See Something, Say Something: Correction of Global Health Misinformation on Social Media. Health Commun 2017/06/18. 2018 Sep;33(9):1131–1140. PMID:28622038
20. Bode L, Vraga EK. In Related News, That Was Wrong: The Correction of Misinformation Through Related Stories Functionality in Social Media. J Commun 2015;65(4):619–638. [doi: 10.1111/jcom.12166]
21. Nyhan B, Reifler J. Does correcting myths about the flu vaccine work? An experimental evaluation of the effects of corrective information. Vaccine 2015; [doi: 10.1016/j.vaccine.2014.11.017]
22. Vraga EK, Bode L. I do not believe you: how providing a source corrects health misperceptions across social media platforms. Information, Commun Soc Routledge; 2017;21(10):1337–1353. [doi: 10.1080/1369118x.2017.1313883]
23. Broniatowski DA, Jamison AM, Qi SH, AlKulaib L, Chen T, Benton A, Quinn SC, Dredze M. Weaponized health communication: Twitter bots and Russian trolls amplify the vaccine debate. Am J Public Health 2018;108(10):1378–1384. PMID:30138075
24. Allem J-P, Ferrara E. Could Social Bots Pose a Threat to Public Health? Am J Public Health 2018 Aug;108(8):1005–1006. PMID:29995482
25. Betsch C, Brewer NT, Brocard P, Davies P, Gaissmaier W, Haase N, Leask J, Renkewitz F, Renner B, Reyna VF, Rossmann C, Sachse K, Schachinger A, Siegrist M, Stryk M. Opportunities and challenges of Web 2.0 for vaccination decisions. Vaccine 2012;30(25):3727–3733. [doi: 10.1016/j.vaccine.2012.02.025]
26. Moher D, Liberati A, Tetzlaff J, Altman DG, Altman DG, Antes G, Atkins D, Barbour V,

Barrowman N, Berlin JA, Clark J, Clarke M, Cook D, D'Amico R, Deeks JJ, Devereaux PJ, Dickersin K, Egger M, Ernst E, Gøtzsche PC, Grimshaw J, Guyatt G, Higgins J, Ioannidis JPA, Kleijnen J, Lang T, Magrini N, McNamee D, Moja L, Mulrow C, Napoli M, Oxman A, Pham B, Rennie D, Sampson M, Schulz KF, Shekelle PG, Tovey D, Tugwell P, Group TP. Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. PLoS Med Public Library of Science; Jul 21, 2009 p. e1000097. PMID:19621072

27. Eysenbach G, Powell J, Kuss O, Sa E-R. Empirical studies assessing the quality of health information for consumers on the World Wide Web: A systematic review. J Am Med Assoc 2002;287(20):2691–2700. [doi: 10.1001/jama.287.20.2691]
28. Barratt H, Rojas-García A, Clarke K, Moore A, Whittington C, Stockton S, Thomas J, Pilling S, Raine R. Epidemiology of Mental Health Attendances at Emergency Departments: Systematic Review and Meta-Analysis. Abe T, editor. PLoS One Public Library of Science; 2016 Apr 27;11(4):e0154449. [doi: 10.1371/journal.pone.0154449]
29. Rojas-García A, Turner S, Pizzo E, Hudson E, Thomas J, Raine R. Impact and experiences of delayed discharge: A mixed-studies systematic review. Heal Expect Feb, 2018 p. 41–56. [doi: 10.1111/hex.12619]
30. Abukaraky A, Hamdan A, Ameera M, Nasief M, Hassona Y. Quality of YouTube TM videos on dental implants. Med Oral Patol Oral y Cir Bucal 2018 Jul;23(4):0–0. [doi: 10.4317/medoral.22447]
31. Ahmed W, Bath PA, Sbaffi L, Demartini G. Novel insights into views towards H1N1 during the 2009 Pandemic: a thematic analysis of Twitter data. Health Info Libr J 2019; [doi: 10.1111/hir.12247]
32. Al Khaja KAJ, AlKhaja AK, Sequeira RP. Drug information, misinformation, and disinformation on social media: a content analysis study. J Public Health Policy 2018 Aug 24;39(3):343–357. [doi: 10.1057/s41271-018-0131-2]
33. Allem J-P, Ramanujam J, Lerman K, Chu K-H, Boley Cruz T, Unger JB. Identifying Sentiment of Hookah-Related Posts on Twitter. JMIR public Heal Surveill JMIR Publications Inc.; 2017 Oct 18;3(4):e74–e74. [doi: 10.2196/publichealth.8133]
34. Allem J-P, Ferrara E, Uppu SP, Cruz TB, Unger JB. E-Cigarette Surveillance With Social Media Data: Social Bots, Emerging Topics, and Trends. JMIR Public Heal Surveill 2017 Dec 20;3(4):e98. [doi: 10.2196/publichealth.8641]
35. Arseniev-Koehler A, Lee H, McCormick T, Moreno MA. #Proana: Pro-Eating Disorder Socialization on Twitter. J Adolesc Heal 2016 Jun;58(6):659–664. [doi: 10.1016/j.jadohealth.2016.02.012]
36. Basch CHE, Zybert P, Reeves R, Basch CHE. What do popular YouTube(TM) videos say about vaccines? Child Care Health Dev 2017/01/21. 2017;43(4):499–503. PMID:28105642
37. Becker BFH, Larson HJ, Bonhoeffer J, van Mulligen EM, Kors JA, Sturkenboom MCJM. Evaluation of a multinational, multilingual vaccine debate on Twitter. Vaccine 2016 Dec;34(50):6166–6171. [doi: 10.1016/j.vaccine.2016.11.007]
38. Biggs TC, Bird JH, Harries PG, Salib RJ. YouTube as a source of information on rhinosinusitis: the good, the bad and the ugly. J Laryngol Otol 2013 Aug 18;127(8):749–754. PMID:18256747
39. Blankenship EB, Goff ME, Yin J, Tse ZTH, Fu KW, Liang H, Saroha N, Fung IC. Sentiment, Contents, and Retweets: A Study of Two Vaccine-Related Twitter Datasets. Perm J 2018/06/19. 2018;22. PMID:29911966
40. Bora K, Das D, Barman B, Borah P. Are internet videos useful sources of information during global public health emergencies? A case study of YouTube videos during the 2015–16 Zika virus pandemic. Pathog Glob Health 2018;112(6):320–328. [doi: 10.1080/20477724.2018.1507784]
41. Branley DB, Covey J. Pro-ana versus Pro-recovery: A Content Analytic Comparison of Social

Media Users' Communication about Eating Disorders on Twitter and Tumblr. Front Psychol 2017 Aug 11;8(AUG). [doi: 10.3389/fpsyg.2017.01356]
42. Briones R, Nan X, Madden K, Waks L. When Vaccines Go Viral: An Analysis of HPV Vaccine Coverage on YouTube. Health Commun 2012 Jul;27(5):478–485. [doi: 10.1080/10410236.2011.610258]
43. Buchanan R, Beckett RD. Assessment of vaccination-related information for consumers available on Facebook ®. Heal Inf Libr J 2014 Sep;31(3):227–234. PMID:25041499
44. Butler DP, Perry F, Shah Z, Leon-Villapalos J. The quality of video information on burn first aid available on YouTube. Burns 2013 Aug;39(5):856–859. PMID:23273651
45. Cavazos-Rehg PA, Zewdie K, Krauss MJ, Sowles SJ. "No High Like a Brownie High": A Content Analysis of Edible Marijuana Tweets. Am J Heal Promot SAGE Publications Inc.; 2018 May 1;32(4):880–886. [doi: 10.1177/0890117116686574]
46. Chary M, Genes N, Giraud-Carrier C, Hanson C, Nelson LS, Manini AF. Epidemiology from Tweets: Estimating Misuse of Prescription Opioids in the USA from Social Media. J Med Toxicol 2017 Dec 22;13(4):278–286. [doi: 10.1007/s13181-017-0625-5]
47. Chew C, Eysenbach G. Pandemics in the age of Twitter: Content analysis of tweets during the 2009 H1N1 outbreak. PLoS One 2010/12/03. 2010;5(11):e14118. PMID:21124761
48. Covolo L, Ceretti E, Passeri C, Boletti M, Gelatti U. What arguments on vaccinations run through YouTube videos in Italy? A content analysis. Hum Vaccin Immunother 2017 Jul 3;13(7):1693–1699. [doi: 10.1080/21645515.2017.1306159]
49. Dunn AGAG, Leask J, Zhou X, Mandl KDKD, Coiera E. Associations between exposure to and expression of negative opinions about human papillomavirus vaccines on social media: An observational study. J Med Internet Res 2015/06/13. 2015;17(6):e144. PMID:26063290
50. Dunn AG, Surian D, Leask J, Dey A, Mandl KD, Coiera E. Mapping information exposure on social media to explain differences in HPV vaccine coverage in the United States. Vaccine 2017;35(23):3033–3040. [doi: 10.1016/j.vaccine.2017.04.060]
51. Ekram S, Debiec KE, Pumper MA, Moreno MA. Content and Commentary: HPV Vaccine and YouTube. J Pediatr Adolesc Gynecol 2018/11/18. 2018; PMID:30445163
52. Erdem H, Sisik A. The Reliability of Bariatric Surgery Videos in YouTube Platform. Obes Surg 2018 Mar 5;28(3):712–716. [doi: 10.1007/s11695-017-2911-3]
53. Faasse K, Chatman CJ, Martin LR. A comparison of language use in pro- and anti-vaccination comments in response to a high profile Facebook post. Vaccine 2016/10/27. Elsevier; 2016 Nov 11;34(47):5808–5814. PMID:27707558
54. Fullwood MD, Kecojevic A, Basch CH. Examination of YouTube videos related to synthetic cannabinoids. Int J Adolesc Med Health 2016/09/18. De Gruyter; 2018 Aug 28;30(4). PMID:27639268
55. Venkatraman A, Garg N, Kumar N. Greater freedom of speech on Web 2.0 correlates with dominance of views linking vaccines to autism. Vaccine 2015 Mar;33(12):1422–1425. PMID:25665960
56. Gimenez-Perez G, Robert-Vila N, Tomé-Guerreiro M, Castells I, Mauricio D. Are YouTube videos useful for patient self-education in type 2 diabetes? Health Informatics J 2018 Nov 29;146045821881363. [doi: 10.1177/1460458218813632]
57. Goobie GC, Guler SA, Johannson KA, Fisher JH, Ryerson CJ. YouTube Videos as a Source of Misinformation on Idiopathic Pulmonary Fibrosis. Ann Am Thorac Soc 2019 May;16(5):572–579. [doi: 10.1513/AnnalsATS.201809-644OC]
58. Guidry JPD, Jin Y, Orr CA, Messner M, Meganck S. Ebola on Instagram and Twitter: How health organizations address the health crisis in their social media engagement. Public Relat Rev 2017;43(3):477–486. [doi: 10.1016/j.pubrev.2017.04.009]
59. Guidry J, Jin Y, Haddad L, Zhang Y, Smith J. How Health Risks Are Pinpointed (or Not) on Social Media: The Portrayal of Waterpipe Smoking on Pinterest. Health Commun 2016 Jun

2;31(6):659–667. PMID:26512916
60. Guidry JPD, Carlyle K, Messner M, Jin Y. On pins and needles: How vaccines are portrayed on Pinterest. Vaccine 2015/09/01. 2015;33(39):5051–5056. PMID:26319742
61. Hanson CL, Cannon B, Burton S, Giraud-Carrier C. An exploration of social circles and prescription drug abuse through twitter. J Med Internet Res 2013 Sep;15(9):256–267. PMID:24014109
62. Harris JK, Duncan A, Men V, Shevick N, Krauss MJ, Patricia ACR. Messengers and Messages for Tweets That Used #thinspo and #fitspo Hashtags in 2016. Prev Chronic Dis Centers for Disease Control and Prevention (CDC); 2018 Jan;15(1):E01. [doi: 10.5888/pcd15.170309]
63. Haymes AT, Harries V. "How to stop a nosebleed": An assessment of the quality of epistaxis treatment advice on YouTube. J Laryngol Otol 2016 Aug;130(8):749–754. PMID:27345303
64. Helmi M, Spinella MK, Seymour B. Community water fluoridation online: an analysis of the digital media ecosystem. J Public Health Dent 2018 Sep;78(4):296–305. [doi: 10.1111/jphd.12268]
65. Kang GJ, Ewing-Nelson SR, Mackey L, Schlitt JT, Marathe A, Abbas KM, Swarup S. Semantic network analysis of vaccine sentiment in online social media. Vaccine 2017 Jun;35(29):3621–3638. [doi: 10.1016/j.vaccine.2017.05.052]
66. Katsuki T, Mackey TK, Cuomo R. Establishing a Link Between Prescription Drug Abuse and Illicit Online Pharmacies: Analysis of Twitter Data. J Med Internet Res 2015 Dec 16;17(12):e280. [doi: 10.2196/jmir.5144]
67. Keelan J, Pavri V, Balakrishnan R, Wilson K. An analysis of the Human Papilloma Virus vaccine debate on MySpace blogs. Vaccine 2010 Feb;28(6):1535–1540. [doi: 10.1016/j.vaccine.2009.11.060]
68. Keim-Malpass J, Mitchell EM, Sun E, Kennedy C. Using Twitter to Understand Public Perceptions Regarding the #HPV Vaccine: Opportunities for Public Health Nurses to Engage in Social Marketing. Public Health Nurs 2017 Jul;34(4):316–323. [doi: 10.1111/phn.12318]
69. Kim R, Park HY, Kim HJ, Kim A, Jang MH, Jeon B. Dry facts are not always inviting: a content analysis of Korean videos regarding Parkinson's disease on YouTube. J Clin Neurosci 2017 Dec;46:167–170. PMID:28988649
70. Krauss MJ, Grucza RA, Bierut LJ, Cavazos-Rehg PA. "Get drunk. Smoke weed. Have fun.": A Content Analysis of Tweets About Marijuana and Alcohol. Am J Heal Promot 2017 May 17;31(3):200–208. [doi: 10.4278/ajhp.150205-QUAL-708]
71. Krauss MJ, Sowles SJ, Moreno M, Zewdie K, Grucza RA, Bierut LJ, Cavazos-Rehg PA. Hookah-Related Twitter Chatter: A Content Analysis. Prev Chronic Dis 2015 Jul;12:E121. [doi: 10.5888/pcd12.150140]
72. Kumar N, Pandey A, Venkatraman A, Garg N. Are video sharing Web sites a useful source of information on hypertension? J Am Soc Hypertens 2014 Jul;8(7):481–490. [doi: 10.1016/j.jash.2014.05.001]
73. Laestadius LI, Wahl MM, Cho YI. #Vapelife: An Exploratory Study of Electronic Cigarette Use and Promotion on Instagram. Subst Use Misuse 2016 Oct 14;51(12):1669–1673. PMID:27484191
74. Leong AY, Sanghera R, Jhajj J, Desai N, Jammu BS, Makowsky MJ. Is YouTube Useful as a Source of Health Information for Adults With Type 2 Diabetes? A South Asian Perspective. Can J Diabetes 2018 Aug;42(4):395-403.e4. [doi: 10.1016/j.jcjd.2017.10.056]
75. Lewis SP, Knoll AKI. Do It Yourself: Examination of Self-Injury First Aid Tips on YouTube. Cyberpsychology, Behav Soc Netw 2015 May;18(5):301–304. PMID:25965864
76. Loeb S, Sengupta S, Butaney M, Macaluso Jr. JN, Czarniecki SW, Robbins R, Braithwaite RS, Gao L, Byrne N, Walter D, Langford A, Macaluso JN, Czarniecki SW, Robbins R, Braithwaite RS, Gao L, Byrne N, Walter D, Langford A. Dissemination of Misinformative and Biased Information about Prostate Cancer on YouTube. Eur Urol 2018/12/07. 2018 Nov;75(4):564–

567. PMID:30502104

77. Love B, Himelboim I, Holton A, Stewart K. Twitter as a source of vaccination information: Content drivers and what they are saying. Am J Infect Control 2013 Jun;41(6):568–570. [doi: 10.1016/j.ajic.2012.10.016]
78. Martinez LS, Hughes S, Walsh-Buhi ER, Tsou M-H. “Okay, We Get It. You Vape”: An Analysis of Geocoded Content, Context, and Sentiment regarding E-Cigarettes on Twitter. J Health Commun 2018;23(6):550–562. [doi: 10.1080/10810730.2018.1493057]
79. Massey PM, Leader A, Yom-Tov E, Budenz A, Fisher K, Klassen AC. Applying multiple data collection tools to quantify human papillomavirus vaccine communication on twitter. J Med Internet Res Canada; 2016 Dec;18(12):e318. PMID:27919863
80. McNeil K, Brna PM, Gordon KE. Epilepsy in the Twitter era: A need to re-tweet the way we think about seizures. Epilepsy Behav 2012 Feb;23(2):127–130. [doi: 10.1016/j.yebeh.2011.10.020]
81. Menon D, Chelakkot PG, Sunil D, Lakshmaiah A. A cross sectional review of patient information available in the World Wide Web on CyberKnife: fallacies and pitfalls. Support Care Cancer 2017 Dec 5;25(12):3769–3773. [doi: 10.1007/s00520-017-3807-4]
82. Merianos AL, Gittens OE, Mahabee-Gittens EM. Depiction of health effects of electronic cigarettes on YouTube. J Subst Use 2016 Nov 9;21(6):614–619. [doi: 10.3109/14659891.2015.1118565]
83. Meylakhs P, Rykov Y, Koltsova O, Koltsov S. An AIDS-denialist online community on a Russian social networking service: Patterns of interactions with newcomers and rhetorical strategies of persuasion. J Med Internet Res 2014;16(11). [doi: 10.2196/jmir.3338]
84. Morin C, Bost I, Mercier A, Dozon J-PP, Atlani-Duault L. Information Circulation in times of Ebola: Twitter and the Sexual Transmission of Ebola by Survivors. PLoS Curr 2018/09/27. 2018 Aug;10. PMID:30254789
85. Mueller SM, Jungo P, Cajacob L, Schwegler S, Itin P, Brandt O. The absence of evidence is evidence of non-sense: Cross-sectional study on the quality of psoriasis-related videos on YouTube and their reception by health seekers. J Med Internet Res 2019 Jan;21(1):e11935. [doi: 10.2196/11935]
86. Porat T, Garaizar P, Ferrero M, Jones H, Ashworth M, Vadillo MA. Content and source analysis of popular tweets following a recent case of diphtheria in Spain. Eur J Public Heal 2018/08/08. NLM (Medline); 2019;29(1):117–122. PMID:30084926
87. Radzikowski J, Stefanidis A, Jacobsen KH, Croitoru A, Crooks A, Delamater PL, Radzikowski J, Crooks A, Delamater PL, Jacobsen KH, Stefanidis A. The Measles Vaccination Narrative in Twitter: A Quantitative Analysis. JMIR Public Heal Surveill 2016 Jun;2(1):e1. PMID:27227144
88. Schmidt AL, Zollo F, Scala A, Betsch C, Quattrociocchi W. Polarization of the vaccination debate on Facebook. Vaccine 2018/05/19. 2018;36(25):3606–3612. PMID:29773322
89. Seltzer EKK, Horst-Martz E, Lu M, Merchant RMM. Public sentiment and discourse about Zika virus on Instagram. Public Health 2017 Sep;150:170–175. [doi: 10.1016/j.puhe.2017.07.015]
90. Seymour B, Getman R, Saraf A, Zhang LH, Kalenderian E. When advocacy obscures accuracy online: Digital pandemics of public health misinformation through an antifluoride case study. Am J Public Health 2015;105(3):517–523. PMID:25602893
91. Syed-Abdul S, Fernandez-Luque L, Jian WS, Li YC, Crain S, Hsu MH, Wang YC, Khandregzen D, Chuluunbaatar E, Nguyen PA, Liou DM. Misleading health-related information promoted through video-based social media: anorexia on YouTube. J Med Internet Res 2013/02/15. 2013;15(2):e30. PMID:23406655
92. Teufel M, Hofer E, Junne F, Sauer H, Zipfel S, Giel KE. A comparative analysis of anorexia nervosa groups on Facebook. Eat Weight Disord - Stud Anorexia, Bulim Obes 2013 Dec

27;18(4):413–420. [doi: 10.1007/s40519-013-0050-y]

93. Tiggemann M, Churches O, Mitchell L, Brown Z. Tweeting weight loss: A comparison of #thinspiration and #fitspiration communities on Twitter. Body Image 2018 Jun;25:133–138. [doi: 10.1016/j.bodyim.2018.03.002]
94. Tuells J, Martinez-Martinez PJ, Duro-Torrijos JL, Caballero P, Fraga-Freijeiro P, Navarro-Lopez V. [Characteristics of the Videos in Spanish Posted on Youtube about Human Papillomavirus Vaccines]. Rev Esp Salud Publica 2015/05/07. 2015;89(1):107–115. PMID:25946591
95. van der Tempel J, Noormohamed A, Schwartz R, Norman C, Malas M, Zawertailo L. Vape, quit, tweet? Electronic cigarettes and smoking cessation on Twitter. Int J Public Health 2016 Mar;61(2):249–256. [doi: 10.1007/s00038-016-0791-2]
96. Waszak PM, Kasprzycka-Waszak W, Kubanek A. The spread of medical fake news in social media – The pilot quantitative study. Heal Policy Technol Elsevier B.V.; 2018;7(2):115–118. PMID:2000745817
97. Yang Q, Sangalang A, Rooney M, Maloney E, Emery S, Cappella JN. How Is Marijuana Vaping Portrayed on YouTube? Content, Features, Popularity and Retransmission of Vaping Marijuana YouTube Videos. J Health Commun 2018 Apr 3;23(4):360–369. [doi: 10.1080/10810730.2018.1448488]
98. Moreno MA, Ton A, Selkie E, Evans Y. Secret Society 123: Understanding the Language of Self-Harm on Instagram. J Adolesc Heal 2016; [doi: 10.1016/j.jadohealth.2015.09.015]
99. Sicilia R, Lo Giudice S, Pei YL, Pechenizkiy M, Soda P. Twitter rumour detection in the health domain. Expert Syst Appl Elsevier Ltd; 2018;110:33–40. [doi: 10.1016/j.eswa.2018.05.019]
100. Shao C, Ciampaglia GL, Varol O, Yang K-C, Flammini A, Menczer F. The spread of low-credibility content by social bots. Nat Commun 2018;9(1):4787. [doi: 10.1038/s41467-018-06930-7]
101. Lomborg S, Bechmann A. Using APIs for Data Collection on Social Media. Inf Soc 2014; [doi: 10.1080/01972243.2014.915276]
102. Fast I, Sørensen K, Brand H, Suggs LS. Social media for public Health: An Exploratory policy analysis. Eur J Public Health. 2015. [doi: 10.1093/eurpub/cku080]

Supplementary files

Search Query:
((((((((((social media[MeSH Terms]) OR twitter) OR facebook) OR instagram) OR flickr) OR “sina weibo”) OR YouTube) OR reddit) OR pinterest)) AND ((health[MeSH Terms]) OR health)) AND ((((((((((((((((((((((((misinformation[MeSH Terms]) OR information seeking behavior[MeSH Terms]) OR communication[MeSH Terms]) OR health knowledge, attitudes, practice[MeSH Terms]) OR “inaccurate information”) OR “poor quality information”) OR “low quality information”) OR “health misinformation”) OR “misleading information”) OR “seeking information”) OR rumour) OR rumor) OR rumours) OR rumors) OR gossip) OR hoax) OR hoaxes) OR “urban legend”) OR “urban legends”) OR myth) OR myths) OR fallacy) OR fallacies) OR “conspiracy theories”) OR “conspiracy theory”).

Table 1A. Results of search query in PubMed

Blocks		Searches PubMed	Results
Social Media	1	MeSH: Social Media	5624
	2	Free terms: “twitter” OR “facebook” OR “instagram” OR “flickr” OR "sina weibo" OR “YouTube” OR “reddit” OR “pinterest”	6070
	3	1 OR 2	9503
Health	4	MeSH: health	336566
	5	Free terms: health	4346920
	6	4 OR 5	4346920
Misinformation	7	MeSH: misinformation OR information seeking behavior OR communication OR health knowledge, attitudes, practice	378428
	8	Free terms: “inaccurate information” OR “poor quality information” OR “low quality information” OR “health misinformation” OR “misleading information” OR “seeking information” OR rumour OR rumor OR rumours OR rumors OR gossip OR hoax OR hoaxes OR “urban legend” OR “urban legends” OR myth OR myths OR fallacy OR fallacies OR “conspiracy theories” OR “conspiracy theory”	23177
	9	7 OR 8	398955
Results	10	3 AND 6 AND 9	1693

Table 2A. Data extraction sheet

Dimension	Items
Search Quality (SQ)	1. Was search date/period mentioned?

	2. Was search tools mentioned?
	3. Was more than 1 search tool used?
	4. Was search terms mentioned?
	5. Was user engagement mentioned?
	6. Was initial hits reported?
	7. Was posts in more than 1 language assessed?
	8. Was interrater reliability for post selection determined
Evaluation Quality (EQ)	1. Raters blinded for the source
	2. Number of raters reported
	3. More than 1 rater
	4. Interrater reliability figure for evaluation determined
	5. A priori criteria defined for accuracy / A priori criteria defined for evaluation
	6. Criterion standard for evaluation stated and different from personal opinion
Scoring system for methodological quality of quantitative included studies (GQ)	1. Did the study address a clearly focused issue?
	2. Did the authors use an appropriate method to answer their question?
	3. Was the study population clearly specified and defined?
	4. Were measures taken to accurately reduce measurement bias?
	5. Were the study data collected in a way that addressed the research issue?
	6. Did the authors take sufficient steps to assure the quality of the study data?
	7. Was the data analysis sufficiently rigorous?
	8. How complete is the discussion?
	9. To what extent are the findings generalizable to other international contexts?
Scoring system for methodological quality of qualitative included studies (GQ)	1. Were steps taken to increase rigour in the analysis of the data?
	2. Were the findings of the study grounded in/ supported by the data?
	3. Please rate the findings of the study in terms of their breadth and depth.
	4. To what extent does the study privilege the perspectives and experiences of health care professionals and patients/carers that are relevant to comparable health systems
	5. Overall, what weight would you assign to this study in terms of the reliability/ trustworthiness of its findings?
	6. What weight would you assign to this study in terms of the usefulness of its findings for this review?

Table 3A. Summary of Quality Scores

Authors	Year	EQ Score	SQ Score	GQ Score
Abukaraky et al.	2018	71	75	94
Ahmed et al.	2019	83	75	100
Al Khaja et al.	2018	NA	38	56
Allem et al.	2017	NA	50	94
Allem et al.(b)	2017	NA	63	78
Arseniev-Koehler et al.	2016	NA	75	100
Basch et al.	2017	NA	50	78
Becker et al.	2016	NA	63	78
Biggs et al.	2013	67	75	56
Blankenship et al.	2018	43	63	94
Bora et al.	2018	100	63	100
Branley et al.	2017	NA	63	100
Briones et al.	2012	83	75	94
Broniatowski et al.	2018	57	75	100
Buchanan et al.	2014	83	44	94
Butler et al.	2013	71	75	94
Cavazos-Rehg et al.	2018	67	63	94
Chary et al.	2017	50	63	100
Chew et al.	2010	50	75	94
Covolo et al.	2017	NA	38	67
Dunn et al.	2015	83	81	100
Dunn et al.	2017	NA	63	94
Ekram et al.	2018	33	50	83
Erdem et al.	2018	21	50	94
Faasse et al.	2016	NA	38	78
Fullwood et al.	2016	NA	50	39
Garg et al.	2015	14	63	83
Gimenez-Perez et al.	2018	100	44	94
Goobie et al.	2019	83	75	94
Guidry et al.	2017	NA	50	100
Guidry et al.	2016	100	75	94
Guidry et al.	2015	67	75	94
Hanson et al.	2013	100	63	100

Harris et al.	2018	100	63	78
Haymes et al.	2016	100	75	94
Helmi et al.	2018	83	50	94
Kang et al.	2017	43	38	94
Katsuki et al.	2015	83	69	100
Keelan et al.	2010	42	63	100
Keim-Malpass et al.	2017	71	63	94
Kim et al.	2017	50	81	94
Krauss et al.	2017	17	50	94
Krauss et al.	2015	17	63	94
Kumar et al.	2014	100	69	94
Laestadius et al.	2016	58	75	50
Leong et al.	2018	17	69	94
Lewis et al.	2015	NA	63	67
Loeb et al.	2018	33	50	67
Love et al.	2013	50	63	94
Martinez et al.	2018	64	75	94
Massey et al.	2016	36	81	100
McNeil et al.	2012	33	50	100
Menon et al.	2017	33	63	72
Merianos et al.	2016	67	75	94
Meylakhs et al.	2014	NA	43	72
Morin et al.	2018	50	75	89
Mueller et al.	2019	100	63	72
Porat et al.	2019	67	63	78
Radzikowski et al.	2016	NA	88	100
Schmidt et al.	2018	57	75	94
Seltzer et al.	2017	57	88	94
Seymour et al.	2015	57	75	94
Syed-Abdul et al.	2013	50	75	94
Teufel et al.	2013	NA	50	94
Tiggermann et al.	2018	14	63	94
Tuells et al.	2015	83	63	100
van der Tempel et al.	2016	57	75	94
Waszak et al.	2018	43	63	94
Yang et al.	2018	100	75	94

Table 4A. Summary table with objectives and conclusions about misinformation prevalence in social media

Authors	Year	Objectives	Methods	Topic	Social Media Platform	Author's conclusions
Mueller et al.	2019	As little is known about YouTube as a source of information on psoriasis, we aimed to investigate the quality of psoriasis-related videos and, if necessary, point out strategies for their improvement.	Evaluating quality	NCD	YouTube	Two-thirds of the psoriasis-related videos we analyzed disseminate misleading or even dangerous content.
Meylakhs et al.	2014	We explored three research areas: (1) reasons for newcomers to come to an AIDS-denialist community, (2) the patterns of interactions of the community with the newcomers, and (3) rhetorical strategies that denialists use for persuasion in the veracity of their views.	Social Network Analysis (Netnograpy)	NCD	VK	Contrary to the widespread public health depiction of AIDS denialists as totally irrational, our study suggests that some of those who become AIDS denialists have sufficiently reasonable grounds to suspect that something is wrong with scientific theory, because their personal experience contradicts the unitary picture of AIDS disease progression.
Keelan et al.	2010	We describe a novel and promising approach to the surveillance of public opinions and attitudes toward immunization.	Content Analysis	Vaccine	MySpace	The high percentage of negative blogs reflected the controversy over the vaccine during its initial adoption.
Massey et al.	2016	The objectives of our study were to quantify HPV vaccine communication on Twitter, and to develop a novel methodology to improve the collection and analysis of Twitter data.	Sentiment Analysis	Vaccine	Twitter	Using and leveraging social media to detect health trends, as well as communicate important health information, is a growing area of research in public health.
Bora et al.	2018	We critically evaluated YouTube videos about Zika virus available during the recent Zika pandemic	Evaluating Quality	Pandemic	YouTube	A considerable chunk of the videos were misleading. They were more popular (than informative videos) and could potentially spread misinformation. Videos from trust-worthy sources like university/health organizations were scarce.
Kumar et al.	2014	We conducted this cross-sectional study to assess the accuracy and content of YouTube videos on HTN and understand how viewers interact with this online information.	Evaluating Quality	NCD	YouTube	Useful videos had the best overall coverage on the epidemiology, pathogenesis, symptoms, complications, preventions/lifestyle modifications, and pharmacologic treatment of HTN. They had a significantly higher quality and reliability score compared with misleading videos and personal views.
Gimenez-	2018	To evaluate the usefulness of YouTube videos as an	Evaluating	NCD	YouTube	Our analysis of YouTube videos as a tool for diabetes

Perez et al.		educative tool for type 2 diabetes self- management.	Quality			self-management education indicates that the probability of finding videos that relate to AADE7 self-care behaviors is less than 50 percent.
Buchanan et al.	2014	To assess the magnitude, interest, purpose and validity of vaccination-related information on Facebook and to determine whether information varies by site viewpoint.	Sentiment Analysis	Vaccine	Facebook	Facebook, or social media in general, may play a large role in propagation of vaccination misinformation.
Dunn et al.	2015	We sought to measure whether exposure to negative opinions about human papillomavirus (HPV) vaccines in Twitter communities is associated with the subsequent expression of negative opinions by explicitly measuring potential information exposure over the social structure of Twitter communities.	Social Network Analysis	Vaccine	Twitter	The heterogeneous community structure on Twitter appears to skew the information to which users are exposed in relation to HPV vaccines.
Tuells et al.	2015	The objective of this work was to know the characteristics of the YouTube videos in Spanish language related to the human papillomavirus vaccine.	Content Analysis	Vaccine	YouTube	Most of the videos have a favorable opinion towards HPV vaccine, although videos with a negative content were the longest and most viewed.
Helmi et al.	2018	The purpose of this study was to analyze patterns of CWF information dissemination by a network of sources on the web.	Sentiment Analysis	NCD	Different sources	The dominant neutral sentiment of the network may signify that anti- and pro-sides of the debate are viewed as balanced, not just in number but also in quality of information.
Teufel et al.	2013	To analyze the content and culture of anorexia nervosa (AN)-related communication on the current major social network site (SNS) Facebook.	Evaluating Content	Eating Disorder	Facebook	SNS appears to be a relevant way for young females suffering from AN to communicate and exchange disease and health-related ideas.
Faasse et al.	2016	Following a prominent Facebook post about childhood vaccination, language used by participants in a comment thread was analysed using LIWC (Linguistic Inquiry and Word Count).	Content Analysis	Vaccine	Facebook	The current findings indicate, that such irrational and emotional qualities do not typify the argument-style or language of Facebook users who make comments indicating opposition to vaccinations. Instead, the antivaccination comments contained linguistic markers of analytical thinking, characterised by categorical language use, often appearing as factual (or in this case, pseudo-factual) and logically structured statements that mimic valid scientific information.
Ekram et al.	2018	In this observational study we investigated publicly available content regarding the HPV vaccine on the video-sharing Web site YouTube (www.YouTube.com).	Evaluating Content	Vaccine	YouTube	It appears the rhetoric on social media has changed toward mostly anti-vaccine.

Porat et al.	2019	This study analyses content and source of the most popular tweets related to a recent case in Spain where an unvaccinated child contracted and later died from diphtheria.	Content Analysis	Pandemic	Twitter	The vast majority of popular tweets were either informative or personal opinions expressing frustration or humour/ sarcasm.
Menon et al.	2017	The purpose of this study is to assess the quality of videos available in YouTube on CyberKnife.	Evaluating Quality	Treatment	YouTube	This study is a mere cross-sectional analysis ofdata available on YouTube on a specific day. It was assessed by three independent oncologists and very definitely subject to physician prejudice against misinformation. However, it was heartening to note that the company videos were reasonably accurate and well presented as were many institutional videos. A totally unexpected benefit from the exercise was the first hand exposure to the profound trust of the patients on the health care system.
Meriano et al.	2016	This study was conducted to assess the quantity, quality, and reach of e-cigarette health effects YouTube videos, and to quantify the description of positive and negative e-cigarette health effects and promotional content in each video.	Evaluating Content	Drug	YouTube	These unregulated battery-operated products were portrayed as having both negative and beneficial health effects despite inconclusive scientific evidence on the safety of use. For this reason, it is critical to monitor health effects messages on e-cigarettes delivered through YouTube videos and develop appropriate messages to inform consumers about the potential risks associated with product use while mitigating false and misleading information presented.
Loeb et al.	2018	We performed the largest, most comprehensive examination of prostate cancer information on YouTube to date, including the first 150 videos on screening and treatment.	Evaluating Content	NCD	YouTube	Many popular YouTube videos about prostate cancer contained biased or poor-quality information. A greater number of views and thumbs up on YouTube does not mean that the information is trustworthy. Published
Lewis et al.	2015	This study examined the nature and scope of NSSI first aid tips on YouTube using a content analysis to examine 40 NSSI first aid videos.	Evaluating Content	Treatment	YouTube	Efforts to provide good quality health information about NSSI via YouTube may be needed. Similar suggestions for other online platforms have also been reported. Mental health professionals also need to be aware that their clients may be accessing videos similar to the ones found in
Al Khaja et al.	2018	Dissemination of misleading drug information through social media can be detrimental to the health of the public.	Evaluating Quality	Drug	WhatsApp	Majority of the drug- related messages on social media were potentially misleading or false claims that lacked credible evidence to support them.
Kim et al.	2017	This study aimed to evaluate the accuracy of Korean videos regarding Parkinson's disease (PD) on	Evaluating Quality	NCD	YouTube	In conclusion, our study found that only about two-thirds of the Korean videos on PD hosted by

		YouTube and viewers' responses to them.				YouTube provide reliable information. More importantly, the videos with reliable contents were less popular than the videos with misleading information. There were many myths and misconceptions about the etiology and treatment of PD on YouTube, and thus, further efforts are warranted to effectively increase the dissemination of accurate and scientifically proven information on PD to YouTube users.
Guidry et al.	2017	This study examined Ebola-related social media posts by three major health organizations, Centers for Disease Control and Prevention (CDC), World Health Organization (WHO), Medecins Sans Frontieres (MSF, also known as Doctors without Borders), on Twitter and Instagram, focusing on the types of communication that were used during the outbreak, the content and context of these communications, and the responses they elicited from the publics.	Content Analysis	Pandemic	Twitter Instagram	Overall, less than 3 of Instagram posts and just 1 of tweets addressed Ebola-related misinformation, with no significant differences between the three organizations. Given that misinformation about the disease was especially rampant on social media during the outbreak, these results suggest that health organizations may have missed an important opportunity to highlight and correct misinformation.
Chary et al.	2017	The purpose of this study was to demonstrate that the geographic variation of social media posts mentioning prescription opioid misuse strongly correlates with government estimates of MUPO in the last month.	Content Analysis	Drug	Twitter	Mentions of MUPO on Twitter correlate strong- ly with state-by-state NSDUH estimates of MUPO. We have also demonstrated that a natural language processing can be used to analyze social media to provide insights for syndromic toxic surveillance.
McNeil et al.	2012	We sought to explore how seizures are being portrayed on this social networking website and to consider its potential for information dissemination.	Evaluating Content, Social Network	NCD	Twitter	This study demonstrated the prevalence of stigmatizing
Katsuki et al.	2015	In order to better assess NUPM behavior online, this study conducts surveillance and analysis of Twitter data to characterize the frequency of NUPM-related tweets and also identifies illegal access to drugs of abuse via online pharmacies.	Evaluating Content, Social Network Analysis	Drug	Twitter	The study also identifies Twitter as a potential source for information illegally promoting the sale of controlled prescription drugs directly to consumers, which is a concerning observation given the inherent risk of abuse, dependency, and questionable authenticity of medicines provided by online pharmacies who are in violation of applicable law, including the US Ryan Haight Act.
Becker et al.	2016	To gain insight into international public discussion on the paediatric pentavalent vaccine (DTP- HepB-Hib) programme by analysing Twitter messages.	Sentiment Analysis	Vaccine	Twitter	Public messages about DTP-HepB-Hib were characterized by little interaction between tweeters, and by frequent referencing of websites and other information links. Twitter messages can indirectly reflect the public's opinion about major events in the debates about the DTP-HepB-Hib vaccine.

Fullwood et al.	2016	Examination of YouTube videos related to synthetic cannabinoids	Evaluating Content	Drug	YouTube	The content of these consumer videos on YouTube often provide the viewer with access to view a wide array of uploaders describing, encouraging, participating and promoting use.
Hanson et al.	2013	To determine whether people who show signs of prescription drug abuse connect online with others who reinforce this behavior, and to observe the conversation and engagement of these networks with regard to prescription drug abuse.	Evaluating Content, Social Network Analysis	Drug	Twitter	Understanding the prevalence of a problem or issue through social media is a good place to start; however, prevalence data fails to take advantage of the key aspect of social media: social networks and relationships.
Krauss et al.	2017	To explore the sentiment and themes of Twitter chatter that mentions both alcohol and marijuana.	Evaluating Content	Drug	Twitter	Tweets normalizing polysubstance use or encouraging marijuana use over alcohol use are common. Both online and offline prevention efforts are needed to increase awareness of the risks associated with polysubstance use and marijuana use. Key
Garg et al.	2015	We assessed the prevalence of the views supporting a link between vaccines and autism online by comparing YouTube, Google and Wikipedia with PubMed	Social Network Analysis	Vaccine	YouTube	Online communities with greater freedom of speech lead to a dominance of anti-vaccine voices
Krauss et al.	2015	We explored normalization or discouragement of hookah smoking, and other common messages about hookah on Twitter.	Evaluating Content, Social Network Analysis	Drug	Twitter	Educational campaigns about health harms from hookah use and policy changes regarding smoke-free air laws and tobacco advertising on the Internet may be useful to help offset the influence of pro-hookah messages seen on social media
Guidry et al.	2016	Given the health risks and the misperceptions associated with waterpipe smoking, this study focuses on how waterpipe smoking is portrayed and represented on the social media platform Pinterest	Evaluating Content	Drug	Pinterest	This study focused on Pinterest and concluded that Pinterest portrayals of waterpipe smoking are overwhelmingly positive and almost entirely ignore potential health and addiction risks.
Yang et al.	2018	The purpose of the study is to investigate how vaping marijuana, a novel but emerging risky health behavior, is portrayed on YouTube, and how the content and features of these YouTube videos influence their popularity and retransmission.	Content Analysis	Drug	YouTube	The results showed that these videos were predominantly pro-marijuana-vaping, with the most frequent videos being user-sharing. The genre and message features influenced the popularity, evaluations, and retransmission of vaping marijuana YouTube videos.
Haymes et al.	2016	This study aimed to assess the quality of advice contained within YouTube videos on the conservative management of epistaxis.	Evaluating Quality	NCD	YouTube	The quality of information on conservative epistaxis management within YouTube videos is extremely variable. A high search rank is no indication of video quality. Many videos proffer inappropriate and dangerous alternatives advice. We do not

						recommend YouTube as a source for patient information.
Allem et al.	2017	This study describes the sentiment of hookah-related posts on Twitter and describes the importance of debiasing Twitter data when attempting to understand attitudes.	Sentiment Analysis	Drug	Twitter	Posts on Twitter communicating positive sentiment toward hookah could add to the normalization of hookah use and is an area of future research.
Morin et al.	2018	This article presents an analysis of tweets concerning a specific theme: the sexual transmission of the virus by survivors, at a time when there was a great uncertainty about the duration and even the possibility of such transmission.	Sentiment Analysis, Evaluating Content, Social Network Analysis	Pandemic	Twitter	Although numerous studies have shown how this can lead to rumours and disinformation, our research suggest that this relative autonomy makes it possible for Twitter users to bring into the public sphere some types of information that have not been widely addressed.
Leong et al.	2018	To investigate the content, quality and popularity of information about type 2 diabetes avail- able on YouTube.	Evaluating Quality	NCD	YouTube	The quality of identified videos concerning type 2 diabetes was variable, and misleading videos were popular. Further creation and curation of high-quality video resources is required
Dunn et al.	2017	Our aim was to determine whether measures of information exposure derived from Twitter could be used to explain differences in coverage in the United States.	Evaluating Content	Vaccine	Twitter	Measures of exposure to HPV related tweets explained more of the variance in state level HPV vaccine coverage than was explained by socioeconomic factors. Our study suggests that in states where negative opinions about HPV vaccines are popularized by mainstream media, the coverage is often lower than would be expected by socioeconomic differences alone.
Radzikowski et al.	2016	This paper presents a study of Twitter narrative regarding vaccination in the aftermath of the 2015 measles outbreak, both in terms of its cyber and physical characteristics.	Evaluating Content, Social Network Analysis	Vaccine	Twitter	The cyber-physical debate nexus, which connects the cyber narrative in social media to the corresponding geographical space, allows the study of the public's concerns, views, and responses to health-related issues and thus offers a new avenue for exploring health narratives. As these new mechanisms of discourse are emerging, health communications and health informatics have to adapt to these newfound capabilities and challenges.
Harris et al.	2018	We sought to 1) examine and compare the characteristics of senders and the content of tweets using these hashtags and 2) identify characteristics associated with engagement with a thinspo or fitspo tweet.	Evaluating Content, Social Network Analysis	Eating Disorder	Twitter	Characteristics of messages and messengers differed between thinspo and fitspo tweets; thinspo tweets were used for messages about disordered eating. Public health professionals should consider using the thinspo hashtag to reach the thinspo group
Syed-Abdul et	2013	The aim of this study was to investigate anorexia-	Evaluating	Eating	YouTube	Pro-anorexia information was identified in 29.3 of

al.		related misinformation disseminated through YouTube videos	Content	Disorder		anorexia-related videos. Pro-anorexia videos are less common than informative videos; however, in proportional terms, pro-anorexia content is more highly favored and rated by its viewers.
Cavazos-Rehg et al.	2018	To investigate tweets about marijuana edibles for surveillance into the content of edibles-related tweets among individuals socially networking about this topic on Twitter	Evaluating Content, Social Network Analysis	Drug	Twitter	Tweets that normalize/encourage edibles use have potential to increase their popularity among individuals who socially network about this topic. Additionally, the prevalence of tweets about edibles' intense, long-lasting high could have implications for the tailoring of prevention messages that caution potential users against these potential outcomes, which can be important for youth and young adult minorities who were inferred to be disproportionately socially networking about edibles on Twitter.
Ahmed et al.	2019	Our aim was to utilise an indepth method to study a period of time where the H1N1 Pandemic of 2009 was at its peak	Evaluating Content	Pandemic	Twitter	Misunderstandings of medical advice can lead to dangerous consequences and must be understood carefully
Martinez et al.	2018	The current study examined conversations on Twitter related to use and perceptions of e-cigarettes in the United States	Evaluating Content	Drug	Twitter	Our findings reveal that although over half of tweets were positive, a sizeable portion was negative or neutral. We also found that, among those tweets mentioning a stigma of e-cigarettes, most confirmed that a stigma does exist. Conversely, among tweets mentioning the harmfulness of e-cigarettes, most denied that e-cigarettes were a health hazard.
Guidry et al.	2015	This study focused on the social media plat- form Pinterest, analyzing 800 vaccine-related pins through a quantitative content analysis.	Content Analysis	Vaccine	Pinterest	The majority of the pins were anti-vaccine, and most were original posts as opposed to repins.
Chew et al.	2010	We suggest and evaluate a complementary infoveillance approach using Twitter during the 2009 H1N1 pandemic.	Evaluating Content	Pandemic	Twitter	Content analysis indicated resource-related posts were most commonly shared (52.6). 4.5 of cases were identified as misinformation.
Schmidt et al.	2018	The goal was to assess whether users' attitudes are polarized on the topic of vaccination on Facebook and how this polarization develops over time.	Social Network Analysis	Vaccine	Facebook	The existence of echo chambers may explain why social-media campaigns that provide accurate information have limited reach and be effective only in sub-groups, even fomenting further opinion polarization.
Branley et al.	2017	To compare how people communicate about eating disorders on two popular social media platforms Twitter and Tumblr	Content Analysis	Eating Disorder	Twitter and Tumblr	The results inspire hope that there are positive elements to online communication about ED such as inspiring recovery, raising awareness, and challenging societal norms. However, it is vital to

						ensure that pro-ana content is not trivialized or dismissed.
Arseniev-Koehler et al.	2016	The purpose of this study was to investigate Pro-ED Twitter profiles' references to EDs and how their social connections (followers) reference EDs	Evaluating Content, Social Network Analysis	Eating Disorder	Twitter	Findings suggest that profiles which self-identify as Pro-ED express disordered eating patterns through tweets and have an audience of followers, many of whom also reference ED in their own profiles. ED socialization on Twitter might provide social support, but in the Pro- ED context this activity might also reinforce an ED identity
Seltzer et al.	2017	We sought to explore how the image-sharing platform Instagram is used for information dissemination and conversation during the current Zika outbreak	Evaluating Content	Pandemic	Instagram	These insights are useful in assessing fears and public opinion that could allow for more targeted surveillance, education, and intervention. As more individuals are affected and the conversation surrounding Zika evolves it will be important to provide salient information in forums where individuals are already frequent, including social media based image platforms.
Butler et al.	2013	To evaluate the clinical accuracy and delivery of information on thermal burn first aid available on the leading video-streaming website, YouTube	Evaluating Quality	Treatment	YouTube	The current standard of videos covering thermal burn first aid available on YouTube is unsatisfactory. In addition to this, viewers do not appear to be drawn to videos of higher quality
Abukaraky et al.	2018	To examine what YouTube offers patients seeking information on dental implants, and to evaluate the quality of provided information	Evaluating Quality	Treatment	YouTube	Information about dental implants on YouTube is limited in quality and quantity.
Erdem et al.	2018	The aim of this study was to answer the question: Is watching these videos useful to surgeons and patients?	Evaluating Quality	Treatment	YouTube	No misleading information was found
Kang et al.	2017	To examine current vaccine sentiment on social media by constructing and analyzing semantic networks of vaccine information from highly shared websites of Twitter users in the United States; and to assist public health communication of vaccines	Content Analysis	Vaccine	Twitter	Semantic network analysis of vaccine sentiment in online social media can enhance understanding of the scope and variability of current attitudes and beliefs toward vaccines. Our study synthesizes quantitative and qualitative evidence from an interdisciplinary approach to better understand complex drivers of vaccine hesitancy for public health communication, to improve vaccine confidence and vaccination coverage in the United State.
Blankenship et al.	2018	To investigate if tweets with different sentiments toward vaccination and different contents attract different levels of Twitter users' engagement.	Social Network Analysis	Vaccine	Twitter	Engaging social media key opinion leaders to facilitate health education about vaccination in their tweets may allow reaching a wider audience online

Waszak et al.	2018	Our pilot study is an initial attempt to measure a number of the top shared health misinformation stories in the Polish language social media.	Evaluating Content	NCD	Facebook	Analyzing social media top shared news could contribute to identification of leading fake medical information miseducating the society. It might also encourage authorities to take actions such as put warnings on biased domains or scientifically evaluate those generating fake health news
Tiggermann et al.	2018	The aim of the present study was to compare thinspiration and fitspiration communities on Twitter.	Social Network Analysis	Eating Disorder	Twitter	Frequency counts and sentiment analysis showed that although the tweets from both types of accounts focused on appearance and weight loss, fitspiration tweets were significantly more positive in sentiment. It was concluded that the thinspiration tweeters, unlike the fitspiration tweeters, represent a genuine on-line community on Twitter. Such a community of support may have negative consequences for collective body image and disordered eating identity
Love et al.	2013	This study reports a content analysis of posts about vaccinations, documenting sources, tone, and medical accuracy	Social Network Analysis	Vaccine	Twitter	Clinicians must be prepared to address patients entering the clinical environment with opinions and expectations based on social media sources and shared links, possibly including false impressions about adverse effects or unsupported expectations for vaccine effectiveness
Keim-Malpass et al.	2017	The purpose of this study was to evaluate the content of messaging regarding the HPV vaccine on the social media and microblogging site Twitter, and describe the sentiment of those messages.	Evaluating Content	Vaccine	Twitter	Using Twitter to understand public sentiment offers a novel perspective to explore the context of health communication surrounding certain controversial issues
van der Tempel et al.	2016	Individuals seeking information about electronic cigarettes are increasingly turning to social media networks like Twitter. We surveyed dominant Twitter communications about e-cigarettes and smoking cessation, examining message sources, themes, and attitudes.	Social Network Analysis	Drug	Twitter	Our findings show that Twitter users are overwhelmingly exposed to messages that favor e-cigarettes as smoking cessation aids, even when disregarding commercial activity. This underlines the need for effective public health engagement with social media to provide reliable information about e-cigarettes and smoking cessation online
Laestadius et al.	2016	This exploratory study analyzed electronic cigarette content found on the visual social networking service, Instagram, in order to highlight public health challenges created by this content and support understanding of electronic cigarette promotion and usage.	Evaluating Content	Drug	Instagram	Instagram content related to e-cigarettes poses two primary areas for concern: (1) e-cigarette users, brands, and vendors are exposing their followers to e-cigarette content, (2) users themselves may reinforce their identity and community membership as vaper through their creation of content and hashtags.
Broniatowski	2018	To understand how Twitter bots and trolls promote	Content Analysis	Vaccine	Twitter	Accounts unlikely to be bots are significantly less

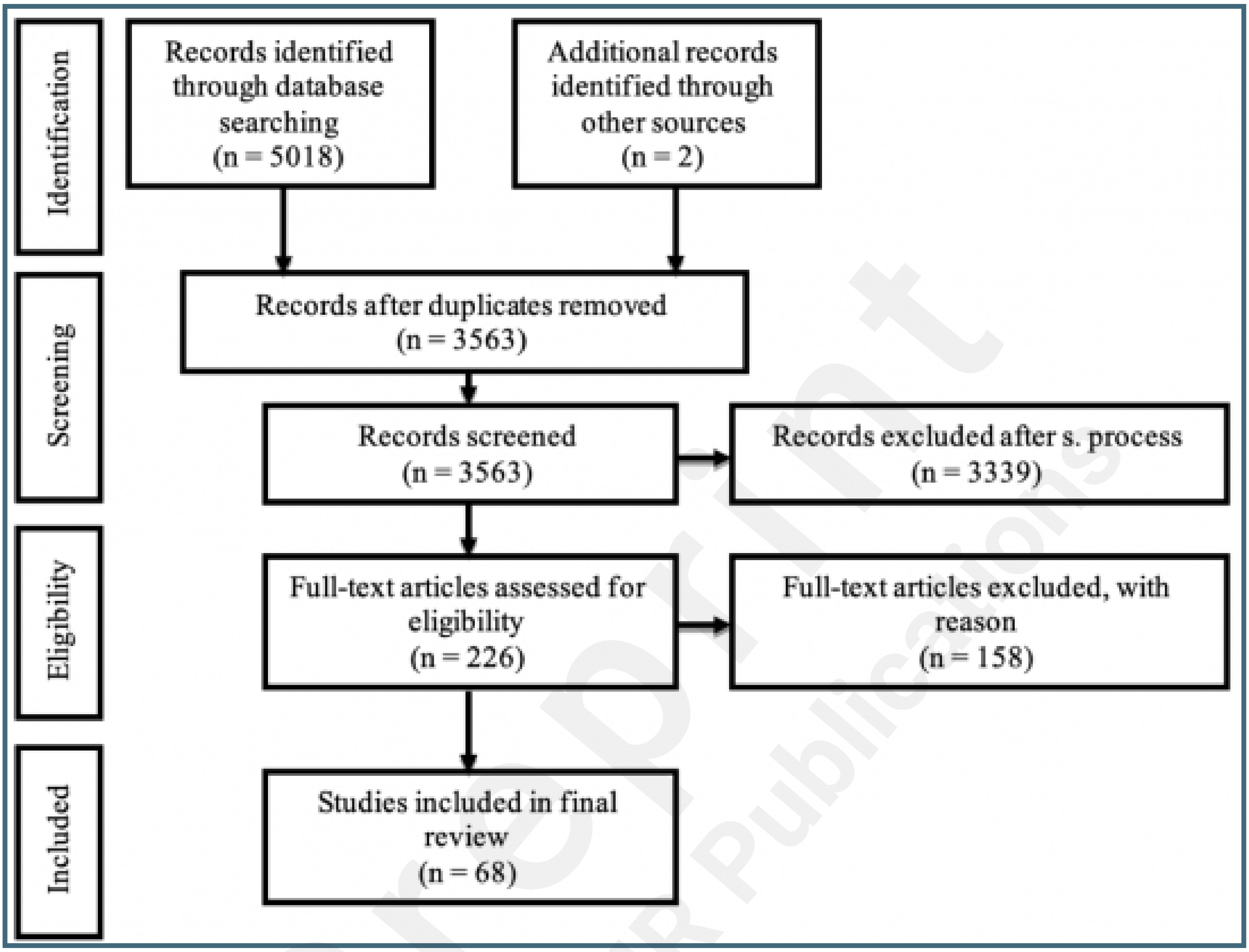
et al.		online health.				likely to promote polarized and antivaccine content. Nevertheless, bots and trolls are actively involved in the online public health discourse, skewing discussions about vaccination.
Covolo et al.	2017	The aim of this study was to explore the message available on YouTube videos about vaccination.	Evaluating Content, Social Network Analysis	Vaccine	YouTube	Considering the increasing use of social media, it would be worth to further investigate how this tool can be used to promote vaccination. It should be also considered that young people are shown to be more sensitive to immunization promotion messages received through social media
Basch et al.	2017	Using the keywords “vaccine safety” and “vaccines and children”, 87 of the most widely viewed YouTube videos were identified and analyzed for content, author status and view count.	Evaluating Content	Vaccine	YouTube	Health professionals should be aware of the widely disseminated vaccination information available on the Internet and should appreciate its possible effect on the public.
Seymour et al.	2015	In an antifluoridation case study, we explored digital pandemics and the social spread of scientifically inaccurate health information across the Web, and we considered the potential health effects	Social Network Analysis	NCD	Facebook	Network sociology may be as influential as the information content and scientific validity of a particular health topic discussed using social media. Public health must employ social strategies for improved communication management.
Briones et al.	2012	This article reports a content analysis of YouTube videos related to the human papillomavirus (HPV) vaccine.	Evaluating Content, Social Network Analysis	Vaccine	YouTube	In conclusion, the results from this study demonstrate that the tone has somewhat shifted on YouTube in terms of the HPV vaccine. Even though most videos were positive only a couple of years ago, more users have since posted content that is more critical of the vaccine. These findings show that YouTube has the potential to shift attitudes and beliefs about a controversial topic such as the HPV vaccine in a relatively short period of time.
Biggs et al.	2013	This study aimed to determine whether YouTube represented a valid and reliable patient information resource for the lay person on the topic of rhinosinusitis.	Evaluating Quality	NCD	YouTube	YouTube appears to be an unreliable resource for accurate and up to date medical information relating to rhinosinusitis. However, it may provide some useful information if mechanisms existed to direct lay people to verifiable and credible sources.
Goobie et al.	2019	We aimed to determine viewer engagement, quality, and content of YouTube videos on IPF and to compare the provided information with contemporaneous guidelines.	Evaluating Quality	NCD	YouTube	Patient-directed YouTube videos on IPF frequently provide incomplete and inaccurate information. Videos supporting the use of non-recommended therapies have higher viewing numbers and user engagement, highlighting the potential risks of using YouTube as a resource for health information.

Allem et al.(b)	2017	This study documents e-cigarette–related discussions on Twitter, describing themes of conversations and locations where Twitter users often discuss e-cigarettes, to identify priority areas for e-cigarette education campaigns. Additionally, this study demonstrates the importance of distinguishing between social bots and human users when attempting to understand public health–related behaviors and attitudes.		Drug	Twitter	Social media data may be used to complement and extend the surveillance of health behaviors including tobacco product use. Social bots may be used to perpetuate the idea that e-cigarettes are helpful in cessation and to promote new products as they enter the marketplace.

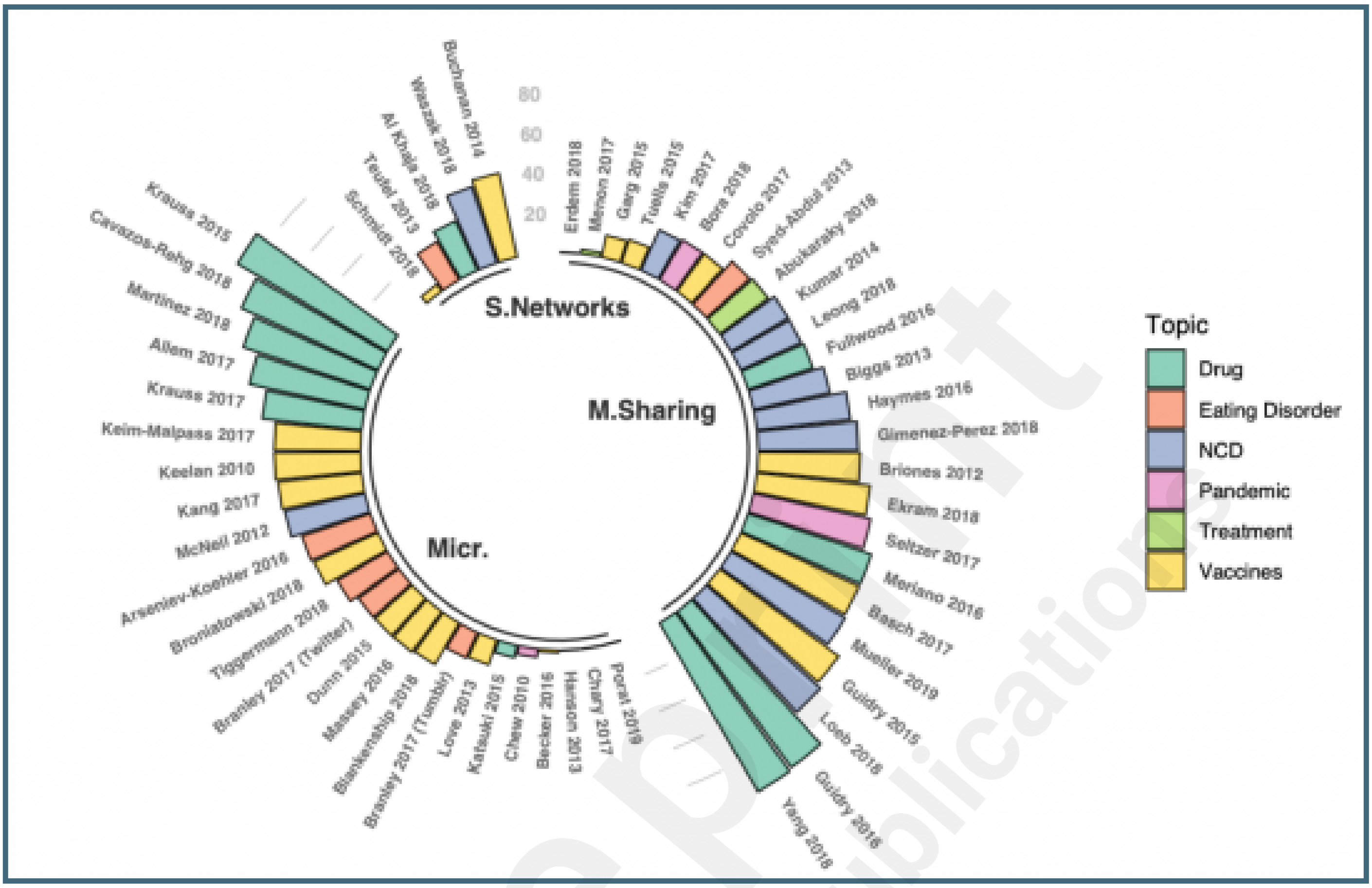
Supplementary Files

Figures

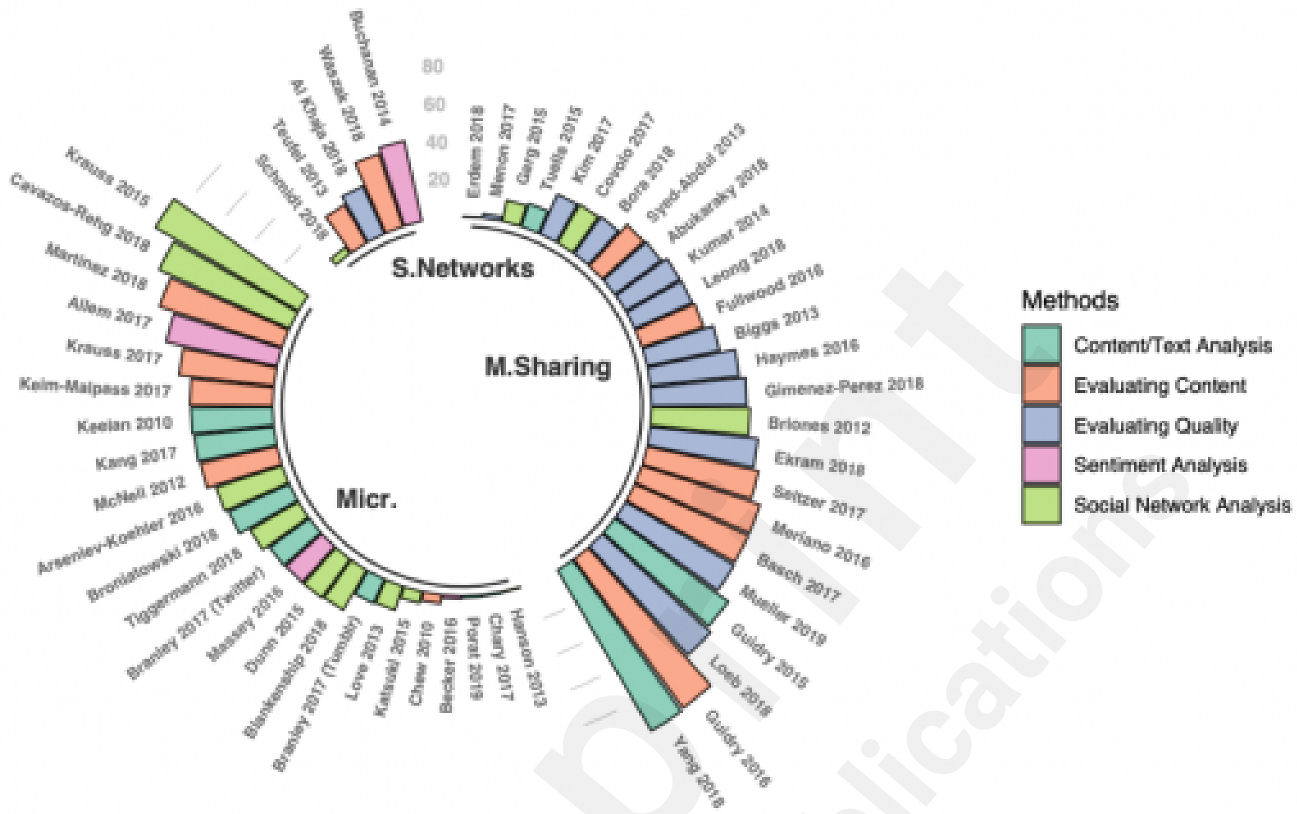
Preferred Reporting Items for Systematic Reviews and Meta-Analyses flow chart.



Prevalence of health misinformation grouped by different topics and social media typology.



Percentage of health misinformation grouped by methods and social media typology.



Multimedia Appendixes

Extraction form.
URL: https://asset.jmir.pub/assets/d7bba08ce6aae510503fb19c40b78d61.docx

Search terms, and results from the search query.
URL: https://asset.jmir.pub/assets/747eb63cfc39d05251b902a96aaa85ef.docx

Objectives and conclusions about misinformation prevalence in social media.
URL: https://asset.jmir.pub/assets/8eb5cba0b2f350e1450cb85ccb5d0319.docx

Summary of Quality Scores.
URL: https://asset.jmir.pub/assets/2a1abbb4d35ed6c71897b19cb379b024.docx