Investigation of Health Misinformation During the Covid-19 Pandemic

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Abstract

This study examines how misinformation related to Covid-19 on social media exacerbates individuals' perceptions of health threats. Informed by the Health Belief Model, we analyze over 5K fact-checked articles to identify different categories or topics of misinformation. We also analyze the veracity and temporal trends of the misinformation topics. Overall, thirteen topics emerged from our analysis, with most of the misinformation questioning the benefits of preventive actions and undermining the severity of the pandemic. We also found significant misinformation related to official sources such as health agencies and research institutes communicating about the pandemic. The findings have implications for social media and health research. Public health experts and policymakers might find insights helpful in designing better communication and intervention strategies to counter the false narrative about the pandemic. The study lays the ground to examine further motivations, mechanisms, and impacts of sharing health misinformation on social media.

Keywords: Social media, Misinformation, Fact-checkers, Health Belief Model, Topic modeling

1. Introduction

Misinformation – content that lacks truth, but the motivation of falsehood is uncertain (Shin et al., 2018) – on social media presents a major concern for the public and society at large. Recently, the vast volume of news and information around the Covid-19 pandemic, which the World Health Organization refers to as "infodemic,"[1] has led to an unprecedented increase in health misinformation. While social media sites assume responsibility for moderating the platforms towards more meaningful and trustworthy content (for instance, see the joint statement from Facebook, Twitter, Google, YouTube, and others to combat fraud and misinformation about Covid-19[2]), the health misinformation woven into online narratives spread too far before any professional source can debunk the information to convince audiences of its inauthenticity. The extant research also suggests that fake news spreads "significantly farther, faster, deeper, and more broadly" than true news (Vosoughi et al., 2018, p. 1146) and has had major implications on society (Ingram, 2018). Furthermore, online narratives, particularly on social media, are fundamental to how people construct socially shared belief systems and can be the primary means to spread misinformation and influence health behaviors (Husna, 2021).

Recent scholarship has examined the structure and motivation of sharing misinformation on social media (e.g., King & Wang, 2021; Kirkwood & Minas, 2020). Scholars have also begun to analyze the harms caused by misinformation, especially during a health crisis or pandemic (Olan et al., 2022; Tran et al., 2021). However, there is a lack of research on how misinformation shared on social media exacerbates the public's perception of health threats. Such an inquiry is warranted, especially during health pandemics, as false social media narratives about the origin or remedies can influence public health attitudes and behavior (Husna, 2021), potentially costing billions of dollars and numerous lives. For instance, the Centers for Disease Control and Prevention (CDC) reports a sharp increase in poisoning cases related to cleaners and disinfectants in the US after the Covid-19 outbreak[3]. Thus, in this study, we are motivated to synthesize the perceptions of health threats that manifest through misinformation shared on social media. Specifically, we answer the following research question: *How does misinformation on social media exacerbate individuals' perceptions of health threats?*

We crawled six fact-checking websites to collect Covid-19 misinformation data. We applied a topic modeling algorithm to identify the misinformation

[1] https://www.who.int/dg/speeches/detail/munich-security-conference
[2] https://www.businessinsider.com/facebook-google-youtube-microsoft-reddit-twitter-fight-coronavirus-covid19-misinformation-2020-3
[3] https://www.cdc.gov/mmwr/volumes/69/wr/mm6916e1.htm?s_cid=mm6916e1_e&deliveryName=USCDC_921-DM26275

URI: https://hdl.handle.net/10125/103305
978-0-9981331-6-4

topics, which were then interpretively mapped to the constructs of the Health Belief Model (HBM) (Houlden & Veletsianos, 2021; Janz & Becker, 1984). The HBM is widely used to understand individuals' behavioral outcomes based on their perception of health threats. Overall, thirteen topics emerged from our analysis, with most of the misinformation questioning the benefits of preventive actions such as masking or social distancing and undermining the severity of the pandemic. We also found much misinformation about sources such as the government, health agencies, and research institutes. Additionally, we observed certain temporal trends in misinformation topics. The findings have implications for social media and health research. Public health experts and policymakers might find insights helpful in designing better communication and intervention strategies to counter the false narrative about the pandemic. This study also lays the ground to examine further motivations, mechanisms, and impacts of sharing health misinformation.

2. Misinformation and social media

Several definitions and conceptualizations of misinformation have been proposed in the extant literature. Shin et al. (2018) define misinformation as information that lacks truth but is uncertain regarding the motivation of falsehood. This conceptualization is usually in contrast with disinformation that is intended to deceive and mislead the public on purpose (Colliander, 2019; Wu et al., 2019). Others use the term fake news, that is, news that contains false or inaccurate information (Singh et al., 2021). Yet others associate misinformation with spamming and rumors to distinguish between verified and unverified information (Colladon & Gloor, 2019; Wu et al., 2020). Although the different conceptualizations have some distinctions, it is rather difficult to differentiate these terms due to the uncertainty about the intent. Thus, following Shin et al. (2018), we conceptualize misinformation as an umbrella term for any type of information that lacks truth, including rumor, spam, fake news, and disinformation.

Recently scholars have begun to examine the phenomenon of misinformation on social media. Overall, two streams of research have begun to emerge. The first stream, grounded in behavioral research, examines the motivations to share misinformation. User belief is noted to be one fundamental reason to spread misinformation. For instance, Kirkwood and Minas (2020) examine individual responses to fake and true news depending on whether a user believes it or not. This study shows that misinformation triggers more appetitive responses, such as spending more time on social media. Further misinformation believed to be true elicits an aversive or avoidance response. Others have also examined the harms caused by misinformation (Karami et al., 2021; Olan et al., 2022; Tran et al., 2021) and interventions to improve information reliability and prevent the dissemination of misinformation, for instance, utilizing expert ratings to increase information credibility (Kim et al., 2019) and psychological factors such as criticism to prevent further propagation (Tanaka et al., 2013). However, such interventions, also called fact-checking, have shown mixed results. For instance, Colliander (2019) notes that using a disclaimer by social media platforms to alert individuals about fake news does not lower one's intention to share misinformation. Others report that flagging misinformation influences user participation, such as commenting and sharing (Kim et al., 2019).

The second stream, grounded in design science tradition, has proposed models to detect and prevent misinformation. The modality of misinformation on social media varies from simple text to images and videos. Accordingly, machine learning algorithms have been proposed to detect fake news (Gravanis et al., 2019; Singh et al., 2021), particularly utilizing features such as sentiment, amount of information, and vocabulary density (King & Wang, 2021; Osatuyi & Hughes, 2018). Others have examined networked patterns of false and true information (Serrano & Iglesias, 2016; Sicilia et al., 2018).

While the existing research has enhanced our understanding of the motives and structure of misinformation, little research has examined how misinformation during a health pandemic such as Covid-19 exacerbates individuals' perceptions of health threats. Such an investigation is important to understand how public health attitudes and behaviors are influenced by misinformation, which is a systemic feature of online health communication and media discourse (Broniatowski et al., 2022; Evanega et al., 2020). Further, the findings could help health agencies design interventions to denounce the false narrative and promote pro-health behaviors

3. Theory of health belief model

The Health Belief Model (HBM), grounded in psychological and social theory, is widely used as a conceptual framework to understand the individual's health behavior (Janz & Becker, 1984). The HMB explains the behavioral outcomes based on two factors: 1) an individual's desire to prevent health threats and 2) an individual's perception of the effectiveness of the behavior adopted to prevent health threats. The perception of threat is further determined by *perceived severity* – an individual's belief that the health threat would have potentially serious consequences and *perceived susceptibility* – individuals regard themselves as susceptible to a condition that might increase their chances of getting sick. The effectiveness of health behavior is determined by the interaction between *perceived benefits* – individuals believe that a particular course of action will lead to some positive outcomes along with reducing the severity or susceptibility to the health threat and *perceived barriers* – individuals perceive few negative attributes related to a particular health behavior (Conner & Norman, 2017; Strecher & Rosenstock, 1997). Additionally, early formulations of the HBM have examined individual health behavior triggered by certain prompts and events (Champion & Skinner, 2008; Hochbaum, 1958). Referred to as *action cues*, these could be triggered internally, for example, through physical symptoms, or externally, for example, through health advisory and mass media.

The HBM has been applied to explain health behaviors in several contexts ranging from the Zika outbreak (Casapulla et al., 2018) to SARS (Leppin & Aro, 2009), H1N1 (Durham et al., 2012), and, more recently, the Covid-19 pandemic (Sheppard & Thomas, 2021). Overall, research suggests that when people are convinced of the severity of health threats, their perception of vulnerability to the infection increases. Further, people are more willing to adopt a recommended behavior if assured of its effectiveness. The framework also has been applied to explain public health beliefs and perceptions toward interventional policies, like lockdown (Czeisler et al., 2021) and social distancing (Raamkumar et al., 2020), and to guide the patient communication of community pharmacists (Sheppard & Thomas, 2021). Others have also examined the public perceptions of health misinformation. For instance, Roozenbeek et al. (2020) note that increased susceptibility to misinformation negatively affects people's compliance with public health guidance and their willingness to get vaccinated and recommend the vaccine to their friends and family.

In this study, we adopt the HBM as a theoretical lens to analyze how misinformation about the ongoing Covid-19 pandemic on social media exacerbates individuals' perceptions of health threats. False messages could alter an individual's health behavior if the messages lead one to believe that they are (not) susceptible to the virus., that the exposure would (not) have potentially serious consequences, that a course of action (such as vaccination or masking) would (not) be beneficial in reducing the susceptibility to or severity of the exposure, and that anticipated benefits of taking action (does not) outweigh the barriers to or cost of action. To that end, we analyze the misinformation to identify specific types of messages related to the different HBM constructs. We discuss our approach to collecting and analyzing the data in the next section.

4. Research methodology

4.1. Data collection and processing

We collected data from January 2020 – when the World Health Organization (WHO) announced the emergence of coronavirus-related pneumonia in Wuhan, China – to August 2020 – when Covid-19 peaked and was declared the third leading cause of death in the US[4]. We wrote customized python scripts to crawl six fact-checking websites: Snopes, PolitiFact, Factcheck.org, Leadstories, AFPfactcheck, and Poynter. Collecting data from fact-checkers is appropriate for our study as it allows us to examine the social media posts flagged as misinformation by verified sources. We analyzed the structure of each fact-checker website to ensure the scripts navigate to an adequate page to extract the data. We used the HTML tags such as Covid-19 and coronavirus to identify and retrieve the articles. We used a python library named *Beautiful Soup* to parse and extract data fields from HTML responses (Richardson, 2007). Overall, we retrieved 5391 articles, each with six attributes: 1) ClaimTitle – the title of an article. 2) Author – the person who published or fact-checked the article. 3) WebDate – published date of the fact-checked article. 4) ClaimDetail – summary of the claim made in the article. 5) Origin – the source of the article, such as Facebook, Twitter, YouTube, WhatsApp, news articles, and Instagram. 6) Veracity – whether an article is false, misleading, or true. For articles that do not provide veracity, we analyzed ClaimDetails to extract the values. Finally, we cleaned the dataset to remove special characters in the retrieved values.

4.2. Data analysis

We applied the topic modeling approach to classifying Covid-19-related misinformation. Topic modeling is an automated approach to examining large bodies of textual data and identifying latent topics or themes represented by a cluster of co-occurring words (Hannigan et al., 2019). Informed by Hannigan et al. (2019), we follow a three-step approach to generate the topic model (also see Syed & Silva, 2022). In the first step, *rendering corpora*, we selected and processed the ClaimTitle and ClaimDetail fields in our dataset. For text transformation, we used the Python package *sklearn* and R text mining package *tm*. Specifically, we decomposed, stemmed, and refined the text following a

[4] A Timeline of COVID-19 Developments in 2020 (ajmc.com)

broad range of content analysis principles, such as focusing on nouns and converting words into word roots (Kobayashi, 2018).

In the second step, *rendering topics*, we applied the Latent Dirichlet Allocation (LDA) algorithm to generate topics. LDA generates topics using statistical probabilities that offer several benefits (Hannigan et al., 2019). For instance, it does not require a pre-defined dictionary or rules for text classification. It also enables identifying hidden themes otherwise not discernable by humans. Finally, it allows for polysemy as the same word can appear in different topics with varying probabilities. Furthermore, LDA is a popular technique used to generate models based on social media data (e.g., Debortoli et al., 2016) and is widely used in information system research (Syed & Silva, 2022).

To fit the best LDA-based model, we used the R package *topic model*. LDA requires two inputs. First is the set of documents to be represented as a document-term matrix (DTM). In our case, each claim was treated as a document, and the DTM contains rows representing claims, columns representing each unique word in the claims, and cells representing the frequency of each word in a particular claim. The second input is the number of topics to be estimated. We used loglikelihood with harmonic mean as a quantitative metric to determine the optimum number of topics (Hannigan et al., 2019). The maximum harmonic mean results indicated that a model with 40 topics was ideal. We also generated and analyzed different models with a varying number of topics. We manually analyzed the top words and the corresponding claims to select the best model. In the final synthesis, we selected the model with 40 topics that were semantically coherent and easier to interpret. Furthermore, we used *topics* function from the *topic model* R package to annotate each fact-checked claim with the most probable topic number to determine the number of relevant fact-checked articles corresponding to 40 topics.

In the third step, *rendering theoretical artifacts*, researchers iterate between theory and the topics of the fitted model to build a new theory or extend an existing theory (Debortoli et al., 2016; Whetten, 1989). Two authors first independently analyzed raw topics as descriptive codes and labeled these topics as first-order codes. The meaning of topics is interpreted by analyzing the most probable ten topic words and the associated text documents (i.e., ClaimTitle and ClaimDetail in our case). We coded all topic labels individually as well as together as an author team, extensively discussed the results, and re-coded the topics when necessary. Next, we grouped these topics into more abstract and second-order codes. Finally, to make sense of the codes against the theoretical background, we mapped the second-order codes to the theoretical constructs of the HBM. We refer to the first and second-order codes derived from our topic-model analysis as sub-topics and topics. In the final synthesis, we derived thirteen Covid-19 misinformation topics.

Additionally, we analyzed the veracity of the emergent topics to determine further which topics are more prone to misinformation. As noted before, in assessing the falsehood of articles, fact-checkers provide veracity, that is, whether an article is false – the primary elements of a claim are demonstrably false, misleading – the primary elements of a claim are demonstrably false, but some of the ancillary details may be true, true – the primary elements of a claim are demonstrably true, or unknown – the veracity cannot be established due to insufficient evidence. Finally, we conducted a temporal analysis of our findings. Specifically, we analyzed how the misinformation topics and their respective veracity evolved over time. We present the results in the next section.

5. Results

Overall, our topic modeling analysis revealed thirteen Covid-19 misinformation categories or topics. Table 1 present a summary of the topics ordered by frequency. Three topics related to *treatments and cures*, *precautions*, and *providers*. The *treatments and cures* was the most dominant topic accounting for 18.09% of claims. This topic promotes remedies and techniques to prevent, treat, or kill the virus. Furthermore, claims misinform about the technology used for diagnostics and vaccine development as well as the approaches to test the presence of virus in humans. The *precautions* topic accounting for 8.93% of claims, provides misinformation about different preventive measures such as face masks, social distancing, lockdowns, and quarantine. This category also provides claims about unproven remedies, such as the consumption of vitamin C and exposure to sunlight to prevent the infection. The *providers* topic related to 3.95% of claims circulates misinformation around the actions or efforts of the healthcare providers. Mainly the claims discuss the ineffectiveness of hospital systems in attending to patients and the supply of essentials such as beds and ventilators. Some claims also discuss the refusal by providers to treat patients and the effects of the virus on providers' health.

Table 1. Misinformation Topics and Sub-Topics

Sample Topic Words	**Sub-Topic (% claims)**	**Topic (% claims)**
Test, result, human, evid, virus, vaccin, develop, cure, prevent,	Vaccines (4.57%), Cures (3.83%), Diagnosis (3.76%),	Treatment and Cures (18.09%)

treatment, effect, water, drink	Remedies (3.37%), Treatment (2.56%)	
infect, Flu, outbreak, symptom, risk, case, confirm, found, warn, refer, peopl, indic	Spread (8.37%), Cases (3.09%), Outbreak (2.54%)	Virus Spread (13.99%)
Health, depart, ministry, govern, order, public, presid, trump, pandem, hous	Health Ministry (3.30%), Government (3.04), Administration (2.83%)	Government (9.17%)
Mask, wear, face, prevent, control, help, measur, lockdown, quarantin, restrict, recommend	lockdown and quarantine (4.50%), Face Masks (3.05%), Preventions (1.38%)	Precautions (8.93%)
Die, person, infect, death, diseas, sarscov, exist, caus, real, suggest	Infection (4.90%), Deaths (3.99%)	Virus Effects (8.89%)
Nation, institut, health, world, organ, fake, deni,confirm, company, virus, product	NIH (3.75%), Companies (3.24%), WHO (1.61%)	Institutes (8.60%)
Relat, india, incid, govern, state, America, unit, work, conspiraci, evid, hoax, citi	Religion (3.72%), Country (3.00%), Conspiracy (1.33%)	Beliefs (8.05%)
fake, messag, inform, clarifi, attribut, offic, statement, china, wuhan, origin, inform, around	Origin (3.74%), Attribution (2.61%)	Virus Source (6.35%)
Offici, statement, issue, hoax, offer, depart, pandem, disease, alleg	Official Announcement (2.74%), Response (2.00%)	Official Response (4.74%)
Doctor, medic, expert, hospit, patient, emerg, support, respons, day, part, alleg	Hospitals (2.58%), Doctors (1.38%)	Providers (3.95%)
Citi, body, report, context, found, polic, men, protest, restrict, offic	Law enforcement (1.89%), Crime (1.44%)	Law and Order (3.33%)
Use, creat, contain, told, famili, account, stori, link, thousand, multipl,time	Advisory (1.28%), Source (1.03%), Message Virality (1.02%)	Media (3.33%)

Report, call, found, suggest, studi, research, sarscov, prove, univers, result	Research (1.96%), Reports (0.61%)	Research (2.58%)

Three other emergent topics referred to *virus spread*, *effect,* and *source*. *Virus spread* accounted for 13.99% of claims and mainly discusses the transmission of the virus among people, increasing cases across different US states and globally, and comparing Covid-19 with other outbreaks such as bird flu, Ebola, and SARS. *Virus effect* accounted for 8.89% of claims and discusses infections caused due to virus mutations and transmissions and associated death counts. *Virus source* accounted for 6.35% of claims and questions about the existence and origin of the virus. Specifically, the claims attribute the cause of Covid-19 to other outbreaks like SARS.

Two other topics related to *government* and *official response*. The *government* topic comprised misinformation related to the actions and recommendations made by government officials and accounted for 9.17% of claims. The *official response* related to 4.74% of claims is associated with the official statements issued by federal and health agencies such as the Center for Disease Control and Prevention (CDC) in response to the pandemic. A related topic that emerged from our analysis was focused on *institutes* which accounted for 8.60% of claims. This topic was mainly comprised of misinformation related to the recommendations, actions, and statements of officials from organizations such as the National Institute of Health (NIH), WHO, and other international health agencies. This topic also referred to claims that debunk tech companies' efforts to disseminate facts, minimize the spread of false information, and remove misleading postings from social media platforms. Another related topic was concerned with *research* accounting for 2.58% of claims. The claims question the findings reported in different research studies conducted on the genome of the Covid virus and promote counter-reports published on online platforms.

Two other topics related to *media* and *law and order* emerged from our analysis, each accounting for 3.33% of claims. The *media* topic provides a narrative about misinformation sources and virality. These claims mainly caution about online social media platforms as a source for the origination of misinformation and the advisories issued through these platforms. The *law and order* topic provides misinformation about the breakdown of the law and the increase in crimes. For instance, people wearing masks break into homes and participate in protests and riots. Finally, the *beliefs* topic accounted for 8.05% of claims. It mainly comprised conspiracy theories such as "force a dangerous and unnecessary vaccine on Americans," "to install tracking devices inside our bodies," and "Bill Gates is behind the coronavirus pandemic." Some claims also discuss religious activities or actions performed by different communities to combat the pandemic.

Table 2 presents the veracity of the thirteen topics. Overall, 82.65% of topics were false, 12.85% were misleading, 2.94% were true, and 1.54% were unknown. The cumulative percentage of false and misleading claims remains consistently higher than true or unknown claims across all topics. Among the misinformation topics, *treatments and cures* and *virus spread* have the highest number of false or misleading claims followed by *precautions* and *providers*. Next, the misinformation about *virus effect*, *government,* and *institutes* are higher, followed by *beliefs* and *virus source*. In comparison, the misinformation related to *official response*, *law and order*, *research*, and *media* remains on the lower end.

Table 2. Topic veracity

Topic	False %	Misleading %	True %	Unknown %
Treatment and Cures	18.21	18.15	17.32	12.4
Virus Spread	13.95	13.99	16.45	11.57
Government	8.92	8.53	18.61	9.92
Precautions	8.58	10.42	10.39	12.40
Virus Effects	8.95	9.03	9.96	2.48
Institutes	8.64	8.83	4.33	12.4
Beliefs	8.53	6.15	5.63	2.48
Virus Source	6.59	6.05	2.16	4.13
Official Response	4.61	4.76	8.23	4.96
Providers	8.58	10.42	10.39	12.4
Law and Order	3.49	2.68	2.16	2.48
Media	3.23	2.48	1.3	19.83
Research	2.41	3.97	1.3	2.48
Total	82.65	12.85	2.94	1.54

Finally, Figure 1 presents the temporal distribution of the misinformation topics, and Figure 2 presents the temporal distribution of the topic veracity. Overall, most of the topics were posted during March and April. The misinformation began to emerge in January and February, spiked its highest during March and April, and started to decline after May. Nevertheless, the proportion of false and misleading topics was higher than true and unknown topics during all eight months.

Interestingly, among the topics, *treatment and cures* was the most prevalent topic during all months of our analysis window. *Treatment and cure* and *virus spread* were the two topics that spiked in February and remained significant through July. Topics such as *virus source*, *virus effect*, *government*, *institutes, official response*, *precautions,* and *beliefs* started to spike in March and remained significant during May, and declined thereafter. Although lower in frequency, the remaining topics, *providers*, *law and order*, *research*, and *media* also spiked during March and April and declined thereafter.

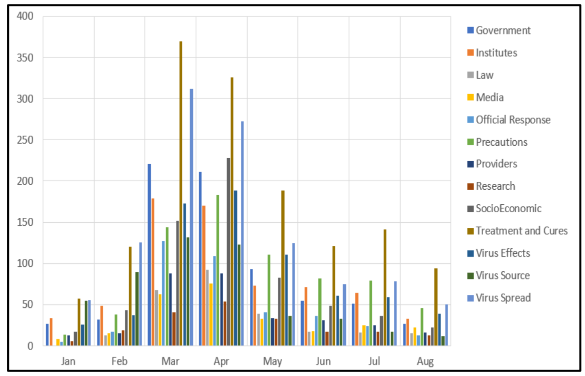

Figure 1. Temporal Analysis of Misinformation topics

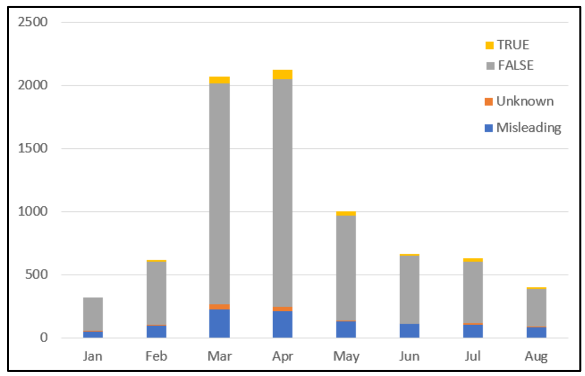

Figure 2. Temporal Analysis of Topic Veracity

6. Discussion & conclusion

In this section, we discuss our findings in relation to the HBM constructs to understand how misinformation on social media exacerbates individuals' perceptions of health threats. As noted before, at the core of the HBM is that health behavior is guided by one's desire to prevent disease and the belief or perception that a specific action will positively impact their health. The health behavior is further determined by *perceived severity* (i.e., belief that the disease would have potentially serious consequences) and *susceptibility* (i.e., perception of increased chances of getting the disease). Furthermore, the effectiveness of the health behavior is determined by *perceived benefits* (i.e., particular actions such as social distancing or vaccination will lead to some positive outcomes along with reducing the severity or susceptibility) and *barriers* to a certain action (i.e., negative attributes related to a particular course of health action). Finally, exposure to *action cues* such as through media or advisories could trigger an individual's health behavior. Our study suggests that all five constructs of the HBM are present in the misinformation claims about Covid-19, although the frequency and veracity vary.

The misinformation intending to influence threat perceptions questioned the severity of the pandemic and susceptibility to infection. The perception of Covid-19 severity was influenced through *virus spread* and *virus effect* topics that together comprised 22.88% of misinformation. While false and misleading claims about *virus spread* were more than *virus effect*, both topics undermine the severity of the disease by providing a false account of the transmission of the virus, rising cases, and health consequences. The perception about susceptibility was influenced through *virus source* and *beliefs* topics that accounted for around 14.4% of misinformation. More false and misleading claims were related to *beliefs* than *virus source*. These claims attribute the virus's origin to other outbreaks and lead individuals to believe that they are immune to the disease through conspiracy theories.

The misinformation intending to influence the perceived effectiveness of recommended measures questioned the benefits and barriers of the measures. The perceived benefits were undermined through *precautions* and *treatment and cure* topics, accounting for 27.02% of misinformation. Both of these topics were highly prevalent and false. The claims undermine the benefits of the precautions suggested by health officials and agencies and promote the benefits of seeking unproven and alternative remedies. The perceived barriers manifested through *law and order* topic, which was comparatively lower in frequency than most other topics and accounted for 3.33% of misinformation. The claims create a negative narrative and a fear about a particular health-promoting action. For instance, masked individuals engage in shoplifting.

Interestingly, our analysis also suggests that misinformation was created to influence individuals' action cues. Specifically, the claims intend to prevent individual action that could be triggered by cues provided by *official response* and *research* accounting for 7.32% of misinformation. Although both topics were lower in frequency, the *official response* had more false and misleading claims than the *research*. These claims undermine statements issued by government and health agencies and the findings reported in research studies. In addition, we found that claims question the sources disseminating information to the public, which accounts for 25.05% of misinformation. Specifically, topics such as *institutes*, *media*, *providers*, and *government* aim to generate a broader mistrust of social institutions that play a critical role in combatting the pandemic. A large number of false and misleading claims related to *providers*, *government*, and *institutes*, with *media* being the lower in frequency.

In terms of the temporal distribution of topics, it is interesting to note that misinformation topics correlated with on-ground events. Overall topics spiked in March and April of 2020 when WHO declared Covid-19 a pandemic and US president Trump declared it a national emergency, and several restrictions were imposed[4]. During this time, misinformation on precautionary measures and alternate remedies started to increase, intending to influence individuals' beliefs about the perceived benefits of measures such as social distancing and shutdowns recommended by the officials. Likewise, mandating masks was related to law and order breakdown, suggesting the ineffectiveness of the perceived barriers. This category emerged in March when some questioned the effectiveness of wearing a face mask to prevent the public from contracting the virus. However, it further spiked in April when federal health officials recommended masks for all people in a public setting[5].

The misinformation about the origin, spread, and effect of the virus also began to spike in February, intending to influence the perception of the severity of the pandemic. While the claims do not downplay the severity of the pandemic, they draw parallels between Covid-19 and previous health crises such as SARS, which is misleading as Covid-19 is transferred more easily[6]. Finally, action cues denouncing health recommendations and advisories spiked during March and April. However, misinformation about federal and health institutes remained prevalent during the entire window of our data analysis.

Based on our findings, we forward the ***Health Belief Misinformation Model (HBMM),*** as shown in Figure 3. According to the model, individuals' health belief is misinformed through *perceived threat alleviation* – claims downplaying the severity and susceptibility to health threat and *perceived ineffectiveness* – claims downplaying the benefits of recommended health actions or measures and barriers or negative attributes related to a particular course of action. This, we argue, will undermine the existence of the health threats and question the efficacy of the precautions and cures to prevent the disease, leading individuals to adopt a lax behavior towards the pandemic. Furthermore, certain claims provide *(in)action cues* to prevent individuals from taking recommended health action or taking alternate action. We hope the model lays the ground for further examining the implications of health misinformation.

[5] Timeline: CDC mask guidelines during the COVID pandemic - Los Angeles Times (latimes.com)

[6] Coronavirus vs. SARS: How Do They Differ? (healthline.com)

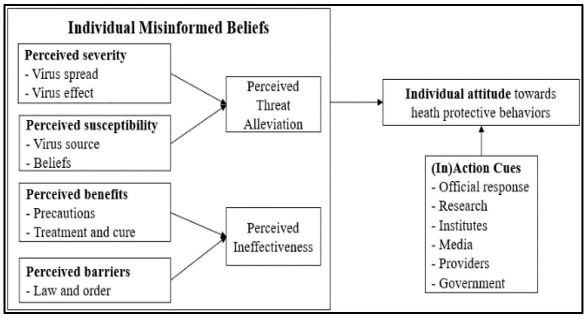

Figure 3. Health Belief Misinformation Model

6.1. Conclusion

In this section, we discuss the contributions of this study to research and practice. We also summarize the limitations of this study and future research opportunities (see Table 3).

Table 3. Findings and Future Research

Findings	Future Research
We found misinformation topics intending to alleviate threat perceptions and influence ineffectiveness perceptions. We also found certain (in)action cues related to federal and health institutions	Future research can examine an individual's self-efficacy, attitude, and behavior upon exposure to health misinformation. Another opportunity is to examine the impact of misinformation on the public's institutional trust.
We found that misinformation veracity varies by topic. For instance, more misinformation was related to *treatment and cures* and less to *research.*	Future research could examine the underlying mechanisms that cause more misinformation on some topics, not others. Another opportunity to examine the motive of sharing certain types of misinformation.
We found the temporal trends in misinformation topics	Future research will examine the trend of misinformation on social media from the beginning of the pandemic to its end and understand the evolution of misinformation. Another opportunity is to analyze the temporality of misinformation campaigns.

This study makes three contributions to the emerging body of research on social media and health misinformation. ***First***, we contribute by developing a taxonomy of misinformation topics that explain how social media is used to question the perceived severity and susceptibility to health threats and the perceived benefits and barriers to effective measures. Further, we forward the HBMM to explain how distinct topics alleviate the perception of health threats and downplay the effectiveness of certain actions and measures. Overall, the model provides a starting point to understand further how misinformation on social media influences individual health behavior. We also identified specific topics such as *government*, *providers*, and *institutes* that provide cues to individual health action or inaction. We argue that this is intended to misplace the trust in health and federal institutions. Future research could thus examine how misinformation impacts the institutional trust of the public.

Second, we contribute by providing insights into the veracity of the misinformation topics. While prior research has examined misinformation using the HBM lens, not much research has examined the intensity of the misinformation. By analyzing the veracity of misinformation topics, we provide insights into how specific HBM constructs are particularly targeted by misinformation campaigns. We found that perceived benefits, for instance, through *treatment and cure* and *precautions* topics, were more misinformed, followed by perceived severity through *virus spread* and *virus effect* topics. We argue that these topics are consequential in influencing the perceptions of health threats and the ineffectiveness of the recommended measures. This opens an opportunity for future research to examine the motive of sharing certain topics. Further, future research could examine the underlying mechanisms that cause more misinformation on some topics than others

Third, we contribute by conducting temporal analysis of misinformation topics. While the frequency of misinformation was higher at the onset of the pandemic and when restrictions were imposed, some topics such as *treatment and cure*, *virus spread*, and *virus effect* remained dominant throughout. Furthermore, we observed a relation between the topics and on-ground events. For instance, there was an increase in *law and order* topic in April 2020 when the mask restrictions were recommended. This suggests that misinformation on social media evolves over time and might be a coordinated campaign. Future research could further examine the temporal evolution of misinformation campaigns.

At the practical level, the findings could help public health experts to understand how misinformation is used to influence individuals' health behavior and, in turn, develop better communication approaches to counter the false narrative around the pandemic. The findings could also help policymakers assess how social media platforms could better manage the spread of misinformation. Furthermore, given the volume and speed at which misinformation is shared on social media, it becomes difficult for public health agencies and officials to analyze the content manually.

Automated analysis of misinformation through natural language processing can be used to classify a large volume of social media content for real-time analysis so that public health agencies and officials can design appropriate interventions to promote protective health behaviors. Using topic modeling, we demonstrated how automated approaches could be used to analyze large volumes of social media misinformation and understand how the misinformation is intended to influence individuals' perceptions.

One of the limitations of this study pertains to the dataset. We extracted the fact-checked articles from six websites - Snopes, PolitiFact, Factcheck.org, Leadstories, AFPfactcheck, and Poynter. Further, the data was collected from January 2020 to August 2020, representing the first wave of the pandemic. In the future, we intend to collect additional data from other sources and for a larger time window that could increase the validity and generalizability of the findings. Furthermore, an extended data collection would allow examining the temporal trends of misinformation topics. Another limitation of this study is that we did not examine whether misinformation influenced the actual behavior of individuals. Thus, in future research, we aim to examine whether exposure to misinformation influences individuals' attitudes toward protective health behaviors, such as not consuming unproven or untested remedies or vaccinating against the disease. Finally, we did not find any topics pertaining to self-efficacy, another construct proposed in recent formulations of the HBM (Champion & Skinner, 2008), which is expected as our dataset pertains to messages targeted toward individuals. Examining self-efficacy would require analyzing how competent or self-efficacious individuals feels to overcome perceived barriers to action upon exposure to misinformation and is a topic for future research.

12. References

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