Computers in Human Behavior 138 (2023) 107487

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Social media may hinder learning about science; social media's role in learning about COVID-19

Sangwon Lee [a,*], Edson C. Tandoc Jr. [b], Edmund W.J. Lee [b]

[a] Department of Communication Studies, New Mexico State University 1405 International Drive, New Mexico State University, Las Cruces, NM, 88003, USA
[b] Wee Kim Wee School of Communication and Information, Nanyang Technological University, Room 02-39, 31 Nanyang Link, 637718, Singapore

ARTICLE INFO

Keywords:
COVID-19
Social media
Science knowledge
Health knowledge
Misinformation
News-finds-me perception

ABSTRACT

Despite widespread concerns that misinformation is rampant on social media, little systematic and empirical research has been conducted on whether and how news consumption via social media affects people's accurate knowledge about COVID-19. Against this background, this study examines the causal effects of social media use on COVID-19 knowledge (i.e., both in the form of factual knowledge and misinformation detection) as well as the underlying mechanisms through which such effects occur. Based on original panel survey data across six weeks (W_1 N = 1,363, W_2 N = 752) in the U.S., we found that consuming news from social media fostered the perception that one need not actively seek news anymore because it would reach them anyway through their social connections (i.e., "news-finds-me" perception). This, in turn, can make one both uninformed and misinformed about COVID-19 issues. Furthermore, this mediated relationship is stronger among those who experience higher levels of information overload while on social media.

Social media is now among the most common tools people use to get news in many countries (Pew, 2018). Thus, it is not surprising that many get information about COVID-19 from social media (Kim & Tandoc, 2021). Ideally, social media can facilitate the dissemination of accurate and reliable health/science information during the pandemic, as experts could rapidly and effectively communicate scientific updates and relevant advice to the audience. However, while social media affordances enable the rapid and wide dissemination of factual information, this also implies that unverified information — either partly inaccurate or completely made-up news — can rapidly spread and reach wide audiences (Vosoughi et al., 2018). Getting accurate and reliable information is crucial for the public, as not doing so may seriously threaten public health.

Despite widespread concerns among journalists and the public that misinformation spreads rapidly and widely through social media platforms, little systematic and empirical research has been conducted on whether and how news consumption via social media affects people's accurate knowledge about COVID-19. To fill the gap, we aim to contribute to the literature in three ways.

First, we examine the relationship between social media news and health/science knowledge (focusing on COVID-19). We conceptualize COVID-19 knowledge broadly as to include both a) factual knowledge about COVID-19 (i.e., to what extent one recalls objective facts about COVID-19-related issues) and b) COVID-19 misinformation detection (i.e., the ability to identify false information regarding various COVID-19-related issues). Existing communication scholarship tends to narrowly conceptualize political/science/health knowledge as to how much one can accurately recall objective facts (i.e., factual knowledge). Yet, as Kuklinski, Quirk, Jerit, Schwieder, and Rich (2000) pointed out, "To be informed requires, first, that people have factual beliefs and, second, that the beliefs be accurate" (p. 792). Scheufele and Krause (2019) also argued that believing incorrect scientific information (i.e., being misinformed) may have more serious consequences than merely not knowing scientific information (i.e., being uninformed). We believe this approach – conceptualizing knowledge both in the form of factual knowledge and misinformation detection – is especially relevant with regard to COVID-19 knowledge, given that COVID-related information entails a large amount of misleading and false information (e.g., Cha et al., 2021; Uscinski et al., 2020) — thus, detecting what is true and what is not is critical to be "informed" about COVID-19.

Second, we examine the underlying causal mechanism behind social media's effect on people's health/science knowledge. To achieve this goal, we will draw on the concepts that have been used to explain the (non-positive or negative) relationship between social media news use

* Corresponding author.
E-mail addresses: swlee@nmsu.edu (S. Lee), edsson@ntu.edu.sg (E.C. Tandoc), edmundlee@ntu.edu.sg (E.W.J. Lee).

https://doi.org/10.1016/j.chb.2022.107487
Received 14 February 2022; Received in revised form 2 September 2022; Accepted 10 September 2022
Available online 14 September 2022
0747-5632/

and factual knowledge, such as information overload (e.g., Bawden & Robinson, 2020) and the news-finds-me perception (Gil de Zúñiga et al., 2017).

Lastly, where prior studies measured misinformation detection with cherry-picked misinformation news items based on their subjective intuition, we systematically constructed misinformation stories and statements based on actual issue saliency. We examined our research questions based on original panel survey data across six weeks.

1. Social media and factual knowledge

Social media plays a central role in health/science communication. For instance, health organizations actively use social media to raise awareness and knowledge of existing health problems and to, motivate health behavior change (Diddi & Lundy, 2017), disseminate critical information during crises or disasters (Eckert et al., 2018; Vos & Buckner, 2016), and engage in real-time surveillance of public health threats by mapping what people are saying or posting on social media (Boulos & Geraghty, 2020). On the individual level, people are becoming more reliant on social media as a health information hub in addition to traditional sources such as television or print newspapers. Survey results from the Pew (2021) showed that more than 80% of those surveyed in the U.S. get their news from digital devices, of which social media was the main platform where young people between the ages of 18–29 obtain their news. It is also well-established that people use social media and online platforms to seek out health information (Van Stee & Yang, 2018).

While the volume of health information—especially pertaining to COVID-19—is generated and disseminated at a high velocity (Lee & Yee, 2020), people who seek COVID-19 news may not necessarily gain more factual knowledge for a couple of reasons. First, the link between social media use and knowledge gains is not clear from existing literature. Research has shown that attention to internet health news sources (including social media) was not significantly associated with elaborative processing, which is a critical antecedent of factual knowledge (Lee et al., 2016). Thus, we expect that seeking COVID-19 information on social media may not motivate people to think deeply and process information systematically and may result in confusion over the veracity of the online COVID-19 information.

Also, new research examining the link between social media use and knowledge has shown that social media may not be efficacious after all in helping individuals learn about COVID-19. Sakya et al. (2021) found that respondents who identified Facebook as their single most trusted or additional source of information were less knowledgeable about COVID-19 as compared with their counterparts who relied on other primary channels of COVID-19 information. Likewise, Granderath, Sondermann, Martin, and Merkt (2020) found that social media use was positively associated with perceived COVID-19 knowledge but not actual knowledge. As such, we postulate:

H1a. Seeking news about COVID-19 via social media is negatively associated with factual COVID knowledge.

2. Social media and misinformation detection

Consistent with our theoretical reasoning that social media use is negatively associated with factual COVID-19 knowledge, we also argue that seeking news about COVID-19 via social media is negatively associated with COVID-19 misinformation detection. In other words, when individuals rely on social media for COVID-19 information, they may be less knowledgeable than their counterparts who do not use social media as much and may be less likely to detect whether a proposition is factual or misinformation. Misinformation is defined as false or inaccurate information—even if it is shared without any ill intentions—that is against the epistemic consensus of the scientific and public health community at a given time (Scheufele & Krause, 2019). Compared with other previous pandemics, COVID-19 is unique such that it is also an *infodemic* (Cinelli et al., 2020), where public health officials and government agencies need to bring the battle to online spaces and address the multitudes of inaccuracies circulating on social media (Mian & Khan, 2020) and the politicization of misinformation while dealing with the physical rampages of the virus. Since the start of the pandemic, various political actors and groups such as President Trump, Qanon, and the controversial Dr. Judy Mikovitz from the documentary "Plandemic" had politicized COVID-19 by making a series of falsehoods about COVID-19's etiology, prevention, and treatment (Viswanath et al., 2020).

Identifying COVID-19 misinformation on social media is a highly complex task. First, there is the problem of "shifting goal-post" in public health guidelines due to emerging findings on COVID-19 (Kim & Tandoc, 2021). Second, the way social media platforms are built makes them inherent risk amplifiers or *amplification stations* (Zhang et al., 2017). Strekalova and Krieger (2017) argued that part of the reasons risks was amplified was because the more users engaged with information, the more posts became viral. If an individual "likes" or reacts to a false COVID-19 claim on social media, it would appear on the social media pages of the individual's online social networks. Also, COVID-19 misinformation could be amplified as users band together online to create a socially constructed version or experience of risks (Strekalova & Krieger, 2017). For example, the politicization of the virus by President Trump by blaming the Chinese has motivated a sub-group of social media users to rally alongside him and post content with the hashtag "Chinesevirus" that further propagated anti-Asian sentiments on social media (Hswen et al., 2021). Lastly, research has shown that misinformation proliferates faster than factual information (Vosoughi et al., 2018), which can significantly increase susceptibility to misinformation. As such, we postulate:

H1b. Seeking news about COVID-19 via social media is negatively associated with COVID misinformation detection.

3. The mediating role of NFMP

While we expect that social media use makes one uninformed and less likely to identify misinformation, an important question to address is *how* this occurs. One potential mechanism why social media, instead of improving knowledge, tends to make people uninformed is the concept of "news-find-me perception (NFMP)." NFMP is defined as "the extent to which individuals believe they can indirectly stay informed about public affairs — despite not actively following the news — through general Internet use, information received from peers, and connections within online social networks" (Gil de Zúñiga et al., 2017, p. 107). While NFMP has been predominantly studied in a political context (e.g., Gil de Zúñiga et al., 2017; Lee, 2020; Song et al., 2016), there are reasons to think that it could be applied in COVID-19 and health/science communication context as well.

In the context of COVID-19, the NFMP phenomenon describes a situation where people do not actively search for COVID-19 online or verify truth-claims because of the belief that they would be exposed to information anyway when they log on to social media. While some studies (Gil-Zuniga et al., 2017; Park & Kaye, 2020) argue that NFMP subsequently increases one's reliance on social media for news (i.e., an individual may stop actively seeking information, believing that using social media will ensure that newsworthy information will reach them regardless), other studies examined what triggers NFMP in the first place. Choosing to seek news from social media rather than from traditional and online news media sources was found to trigger NFMP (Lee, 2020; Song et al., 2016). This may be in part due to how social media platforms are designed to allow for content consumption. Most of the platforms were designed to be a one-stop shop where all the content deemed to be most relevant to individuals is consolidated and automatically pushed to users, thereby de-incentivizing active searches. As such, seeking news about COVID-19 on social media (instead of using traditional and online news media sources) may facilitate NFMP since they do not need to put in much effort to find this information, which is automatically fed to them by the platform based on their past searches, or posts shared by their immediate social networks, which could be detrimental to gaining knowledge.

While NFMP could make people uninformed, such beliefs could also make them misinformed. Discerning COVID-19 facts and misinformation may be difficult, given that specialized knowledge may be required to judge the accuracy of health information (Pennycook et al., 2020). As such, we postulate:

H2. NFMP mediates the relationship between seeking news about COVID-19 via social media and (a) COVID factual knowledge and (b) COVID misinformation detection.

4. The moderating role of information overload

Even though social media's association with NFMP is nascent research, studies have already demonstrated the link between the two (Gil de Zúñiga et al., 2017; Lee, 2020), yet we are cognizant that the relationship may not be universal. One of the factors that may explain the differential outcomes between news information seeking on social media and NFMP is *information overload.* Information overload refers to a state in which "information-processing demands on the individual exceed their capacity to process the information, rendering them unable to process all informational inputs" (Pentina & Tarafdar, 2014, p. 213). In the context of news, information overload refers to the constant and abundant collection of news, as well as the increasing flow of unconfirmed and unreliable information acquired through various media, including social media platforms. A study found that those who receive information about COVID-19 frequently reported experiencing perceived information overload (Mohammed et al., 2021). Studies have found that information overload is likely to discourage people from actively engaging with and elaborating the content (Hong & Kim, 2020; Jensen et al., 2017). In this sense, the concept of information overload can be conceptually related to the assumptions of NFMP, as it also represents one's lack of cognitive involvement with the news.

Based upon this logic, we expect that the relationship between COVID-19 news seeking on social media and NFMP would be particularly stronger among those with higher levels of information overload. That is, while heavy COVID-19 news consumption via social media can produce NFMP in general, we expect the strength of this relationship not to be the same for all users but rather vary based on the extent to which one feels overloaded when processing such news. People overloaded with information will likely develop stronger NFMP, as they would not have enough cognitive energy or motivation to actively and carefully process the content. Instead, they may just think (or even rationalize) that news will find them anyway on their social networks, even if they do not actively seek it. While no study has directly examined the relationship that we are aiming to test, existing empirical studies back up our arguments.

Liu et al. (2021) found that information overload on social media was positively associated with both social media fatigue and fear of COVID-19 information, and both are positively associated with the intention to discontinue using social media. Also, research has shown that information overload was positively associated with the use of heuristic processing and negatively associated with the systematic processing of COVID-19 information (Hong & Kim, 2020). Given the above theoretical rationale and empirical findings, we postulate:

H3. Information overload on social media will moderate the relationship between seeking news about COVID-19 and NFMP, such that the relationship will be stronger for those with higher levels of information overload while on social media.

Based on H2 (mediation hypothesis) and H3 (moderation hypothesis), we aim to construct a theoretical model which employs a holistic approach to explain social media's effect on COVID-19 knowledge. Thus, we introduce the following moderated mediation hypotheses:

H4. :Information overload on social media will moderate the mediating effect of seeking news about COVID-19 on (a) factual COVID-19 knowledge and (b) misinformation detection through NFMP so that the indirect effect will be stronger for those with higher levers of information overload on social media.

5. Method

5.1. Sample

This study draws from a two-wave U.S. national panel survey conducted during the 2020 U.S. presidential election. The U.S. serves as a relevant context to examine our research questions, as a) The U.S. COVID-19 death toll is by far the highest of any country, and b) fake news regarding COVID-19 prevailed during the U.S. election, as the COVID-19 issue has been politicized in the U.S. (Calvillo et al., 2020). Participants were recruited from Dynata, a survey sampling company that has online panels of survey respondents who receive various forms of compensation for participation. This study utilized stratified quota sampling, whereby the sample was matched to the U.S. census.

The first wave of the survey (W1) was conducted from September 26–29, 2020 ($N = 1363$). The second wave (W2) was conducted right after the 2020 U.S. Presidential Election, from November 4–10, 2020 ($N = 752$). The retention rate of 55.2% falls within an acceptable rate for data representation (see Watson & Wooden, 2006). The sample closely mirrored census data on gender, income, and ethnicity but was slightly older compared with the U.S. Census data. There were few differences in the sample composition of the initial and final sample, which alleviated concerns about selection bias (Appendix A). We controlled for common method bias by using a longitudinal design (Podsakoff et al., 2012).

5.2. Measures

Factual COVID knowledge. We assessed factual COVID-19 knowledge by looking at how accurately survey respondents answered a series of factual questions about COVID-19 issues at two-time points. Factual COVID-19 knowledge refers to not only knowledge about science but also about the latest policy and political discussions about COVID-19. Correct responses were coded as 1, while incorrect responses and "Don't know" responses were coded as 0. Correct scores were added to create an index of COVID-19 factual knowledge. For W1, we asked four questions about general COVID-19 knowledge (see Appendix C for the full list of items). For W2, following previous approaches (e.g., Eveland et al., 2005; Lee & Xenos, 2019), respondents were only asked questions about issues and events that occurred between W1 and W2 to a) avoid instrument learning and b) gauge the extent to which the respondents gained new information (four items; see Appendix C).

Misinformation detection. Following previous work (Pennycook et al., 2020), we presented participants with a list of statements, including both true and false statements regarding COVID-19). Participants then were asked to rate the extent to which they think each statement is credible on a five-point scale, ranging from 1 (Definitely false) to 5 (Definitely true). Responses to false statements were reverse-coded and then averaged to form an index of misinformation detection (W1: eight false statements; W2: seven statements; see Appendix C). The false statements were either taken from claims judged false by Snopes.com or Factcheck.org. We also included true stories so that participants will not automatically think that all the presented stories are false. Importantly, we identified the most popular fake news stories circulated on social media at the time of data collection based on an approximate measure of saliency according to the total number of related posts and engagement metrics using CrowdTangle, Facebook's API for researchers. This was accomplished by taking keywords related to the fact-checked statements and entering search terms into the API. We then isolated statements that received more attention in terms of a) higher number of related posts and b) higher engagement numbers. This tool allowed us to construct misinformation stories based on actual issue saliency rather than our intuition.

COVID news use on social media. Participants were asked on a 6-point scale (1 = Never, 6 = Several times a day) to indicate how often they actively sought news about COVID-19 from a) Facebook, b) Twitter, c) YouTube, d) WhatsApp, and e) all of the social media platforms. These items were averaged to create an index of social media news consumption.).

News-Finds-Me perception (NFMP). Participants were asked to indicate their level of agreement with six statements adopted from previous studies (Gil de Zúñiga et al., 2017; Song, Gil de Zúñiga, & Boomgaarden, 2020: e.g., "I do not have to actively seek news because when important public affairs break, they will get to me in social media."

Information overload on social media. Based on Song et al. (2016), participants were asked to indicate to what extent they agree with three statements (e.g., When I am on social media, I feel overloaded with the amount of information I see) to assess information overload.

Control variables. To measure their COVID news consumption, we asked participants on a 6-point scale (1 = never, 6 = several times a day) how often they actively sought news about COVID-19 via (a) print newspapers (W1: M = 2.22, SD = 1.37), (b) radio (W1 = 2.18, SD = 1.27), (c) television (W1: M = 3.09, SD = 1.39), (d) online news (W1: M = 2.82, SD = 1.36), and e) mobile news (W1: M = 1.81, SD = 1.26). We also controlled party affiliation, as the COVID issue has been politicized in the U.S. (Hart et al., 2020). The response options were Republican/Lean Republican (34.4%), Democrat/Lean Democrat (38.8%), Independent (21.0%), and Others (5.7%). Those who identified themselves as Republican/Lean Republican were coded as 1, while others were coded as 0. Lastly, we controlled demographic variables including age (M = 54.34, SD = 16.29), gender (51.3% female), education (assessed as highest level of education completed; Mdn = 4-year college degree), ethnicity (White: 73.5%), and annual household income (Mdn = $70,000 - $79,999).

The means of all scale items are presented in Table 1, and the full wordings of these items are presented in Appendix C.

5.3. Analytic procedure

Using SmartPLS4, we conducted autoregressive Partial Least Squares–Structural Equation Modeling (PLS-SEM) to test the direct, indirect, and conditional indirect effects, as well as confidence intervals, t-values, and p-values of path coefficients. PLS-SEM effectively analyzes complex models with mediation and moderation and stringently test the relationships among all variables of interest as a structure (Henseler & Chin, 2010). The bootstrap estimates are based on 5000 bootstrap samples as suggested by Hair (2010).

The autoregressive approach was used as it allows us to assess how Wave 2 variables are related, while each Wave 2 variable is regressed on its corresponding Wave 1 variable, which enables researchers to explain the unexplained variance in Wave 2 variables while still accounting for variable stability over time. To deal with the missing data, we used the list-wise method, which is known to produce approximate, unbiased regression coefficients. The bootstrap results are shown below in the following tables and figures.

Table 1
Latent variable descriptive statistics.

	Mean	Median	Min	Max	SD
Social media news (W1)	1.68	1.17	1	5	1.01
Information overload (W1)	3.03	3	1	5	1.11
NFMP (W1)	2.52	2.47	1	5	.90
COVID misinformation detection (W1)	2.42	2.35	1	5	.91
COVID knowledge (W1)	.58	.67	0	1	.33
Social media news (W2)	1.70	1.17	1	5	1.05
Information overload (W2)	2.96	3	1	5	1.12
NFMP (W2)	2.58	2.47	1	5	.92
COVID misinformation detection (W2)	2.44	2.46	1	5	.92
COVID knowledge (W2)	.51	.64	0	1	.35

6. Results

Model evaluation in Partial Least Squares–Structural Equation Modeling (PLS-SEM) consists of two stages; the first stage involves an assessment of the measurement model and the second is an assessment of the structural model.

6.1. Measurement model

The measurement model assesses the validity and reliability of the instrument (see Fig. 1). More specifically, it includes the assessment of convergent validity, discriminant validity, and reliability (Hair et al., 2017). The internal consistency reliability was established through the composite reliability (CR). All values were above 0.7, which means that all the constructs are reliable. The indicator reliability was assessed through indicator loadings, most of which are higher than or close to 0.7. The convergent validity of constructs was assessed based on the Average Variance Extracted (AVE). All the constructs' AVE was above 0.5 (Hair et al., 2017), except for the AVE of COVID knowledge at W1 (0.47), which slightly failed to meet the criteria of 0.5, whose value indicates a sufficient degree of convergent validity. Yet, it is rather common as it is measured as a sum of binary variables (correct = 1 vs. incorrect = 0). All values of CR, indicator loadings, and AVE are presented in Table 2. Lastly, to measure the discriminant validity of the latent variables, we adopted the Fornell–Larcker criterion (Fornell & Larcker, 1981). The AVE of each construct was higher than its correlation with other remaining constructs, which shows high discriminant validity. The only exception was the correlation between social media news (W1) and social media news (W2) (see Table 3). Yet, it is understandable as social media news on W1 and W2 are capturing the same construct. We also assessed discriminant validity using HTMT (Henseler et al., 2015). As Table 4 suggests, most of the values in the matrix are lower than 0.85 or 0.9, except for the relationships between COVID knowledge in W1 and W2, and social media news in W1 and W2, which is not surprising as they capture the same constructs. Overall, these values show that the measurement model fit was adequate.

6.2. Structural model

Having met all the assessment conditions for the measurement model, we assessed the structural model using PLS bootstrapping procedures. The structural model determines whether the structural relations in the model are meaningful. First, R2 was used to evaluate the model's explanatory power, and the Stone-Geisser Q2 was used to assess the predictive relevance of the inner model (see Table 5). First, the R-squared (R2) values, which are all above 0.20, indicate the model's enough explanatory power. In addition, the Stone-Geisser Q^2 values obtained through the blindfolding technique also suggest that our model has moderate to strong predictive power as cross-validated redundancy Q2 for all variables were higher than 0.15 (For a better understanding of the interpretation, see the rules of thumb given in Hair et al., 2017). Lastly, the SRMR value is typically used as a goodness of fit measure for PLS-SEM. The SRMR value of the model is 0.78, which meets the criteria of a good model. On this basis, we now turn to the hypotheses testing.

6.3. Hypotheses testing

The first set of hypotheses predicted that social media news use would be negatively associated with COVID-19 factual knowledge (H1a)

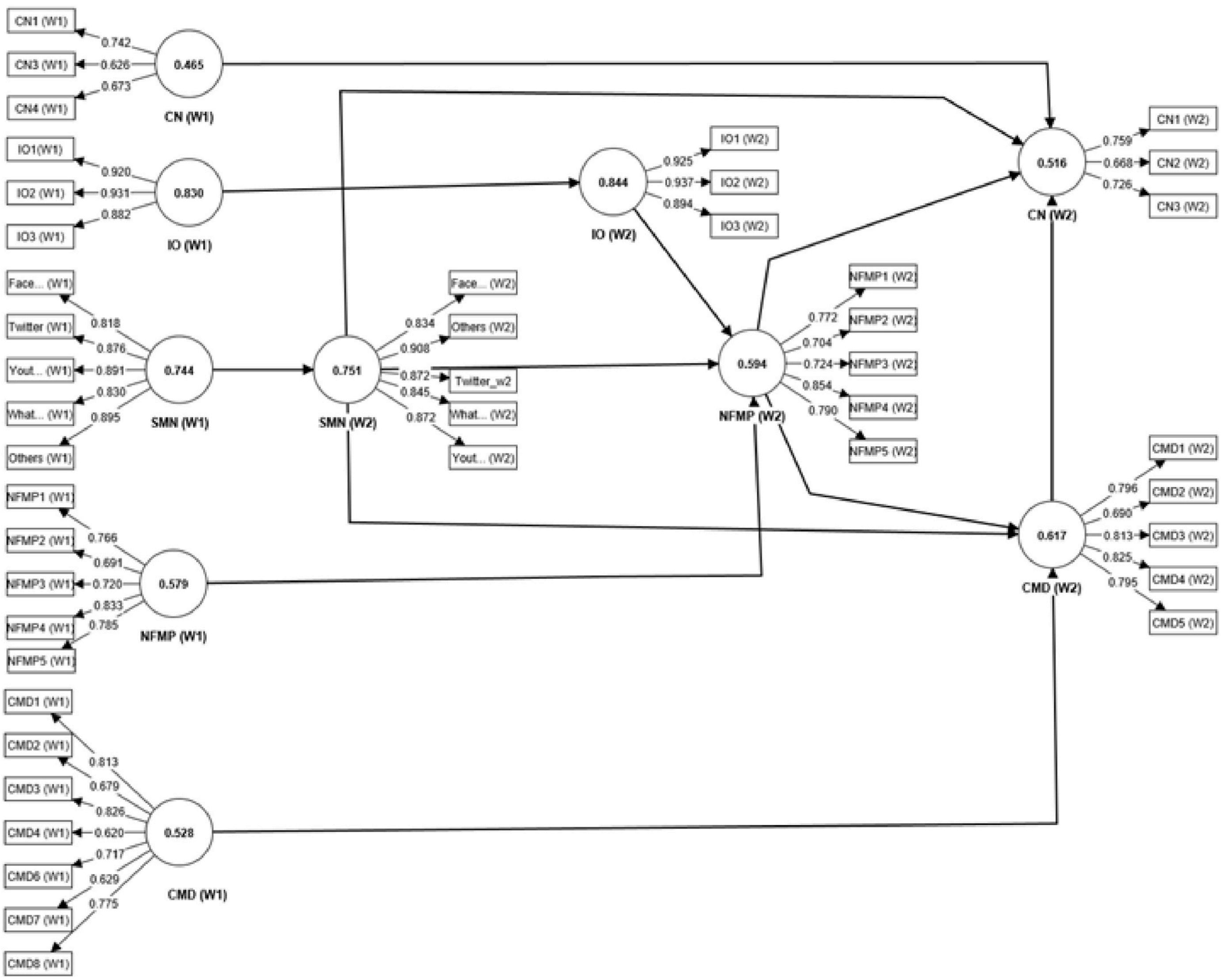

Fig. 1. Measurement Model Assessment

Notes. The values above the arrows indicate factor loadings. The values inside the circles indicate the AVEs of the constructs.

and COVID misinformation detection (H1b). The results suggest that social media is not significantly associated with COVID-19 factual knowledge ($\beta = -0.03$, $p = .57$) while negatively associated with an ability to detect COVID misinformation ($\beta = -0.16, p <. 001$; see Fig. 2). Thus, H1 is partially supported.

The second set of hypotheses stated that the relationship between social media news and two different types of COVID-19 knowledge —factual knowledge (H2a) and misinformation detection (H2b) — would be mediated by NFMP. The results suggest that social media news use was positively associated with NFMP ($\beta = 0.17$, $p < .001$) and that NFMP was strongly negatively associated with factual knowledge (W2) ($\beta = -0.12$, $p = .001$) and misinformation detection (W2) ($\beta = -0.11$, $p = .001$). Further mediation analysis also indicates the mediating mechanism is statistically significant), since the confidence interval does not include zero (factual knowledge: $b = -0.02$, $SE = 0.01$, bootstrapping CI = [-0.05, -0.01]; misinformation detection: $b = -0.02$, $SE = 0.01$, bootstrapping CI = [-0.04, -0.01]).

H3 tested the dsinteraction effect between social media news use and information overload on NFMP. As predicted, social media news use significantly interacted with information overload in predicting NFMP ($B = 0.09$, $p = .007$). In other words, the relationship between social media news use and NFMP became stronger as levels of information overload increased. Thus, H3 is supported.

H4 stated that information overload on social media would moderate the mediating effect of social media news use on two different types of COVID-19 knowledge through NFMP.

As predicted, there was a significant moderated mediation effect as can be seen in Table 6. In other words, the indirect effect turned out to be stronger for those who reported higher levels of information overload while on social media. The full model is also presented in Fig. 2. Thus, H4 is supported.

6.4. Additional analysis

In addition to the autoregressive SEM approach, we also conducted fixed-effects SEM analysis, as the autoregressive approach only allows researchers to estimate the change scores at the aggregate level. Thus, to gauge individual-level change we also used the fixed effects approach, where we calculated the raw difference score (i.e., subtracting the Wave 1 score from the Wave 2 score) for the variables used in the model (Shah et al., 2005). The fixed-effects PLS-SEM approach showed that model's predictive relevance was unacceptable based on Stone Gaizer's Q^2 (below 0.02) (see Appendix D); thus the model was not adopted. We discuss the limitations in the discussion section.

Table 2
Construct validity and reliability.

Latent Construct	Indicator	Indicator Loading	CR	AVE
Social Media News (W1)	Facebook (W1)	.818	.936	.744
	Twitter (W1)	.876		
	Whatsapp (W1)	.83		
	Youtube (W1)	.891		
	Others (W1)	.895		
Information Overload (W1)	IO1(W1)	.92	.936	.83
	IO2 (W1)	.931		
	IO3 (W1)	.882		
NFMP (W1)	NFMP1 (W1)	.776	.872	.578
	NFMP2 (W1)	.691		
	NFMP3 (W1)	.719		
	NFMP4 (W1)	.835		
	NFMP5 (W1)	.774		
COVID Knowledge (W1)	CN1 (W1)	.742	.722	.465
	CN3 (W1)	.626		
	CN4 (W1)	.673		
COVID Misinformation Detection (W1)	CMD1 (W1)	.813	.886	.528
	CMD2 (W1)	.679		
	CMD3 (W1)	.826		
	CMD4 (W1)	.62		
	CMD6 (W1)	.717		
	CMD7 (W1)	.629		
	CMD8 (W1)	.775		
Social Media News (W2)	Facebook (W2)	.833	.938	.751
	Twitter (W2)	.873		
	Whatsapp (W2)	.845		
	Youtube (W2)	.872		
	Others (W2)	.907		
Information Overload (W2)	IO1 (W2)	.925	.942	.844
	IO2 (W2)	.936		
	IO3 (W2)	.894		
NFMP (W2)	NFMP1 (W2)	.813	.863	.594
	NFMP2 (W2)	.721		
	NFMP3 (W2)	.733		
	NFMP4 (W2)	.857		
	NFMP5 (W2)	.79		
COVID Knowledge (W2)	CN1 (W2)	.759	.762	.516
	CN2 (W2)	.668		
	CN3 (W2)	.726		
COVID Misinformation Detection (W2)	CMD1 (W2)	.795	.889	.617
	CMD2 (W2)	.689		
	CMD3 (W2)	.814		
	CMD4 (W2)	.825		
	CMD5 (W2)	.796		

7. Discussion

While studies have found that social media news use has negative effects on factual knowledge (e.g., Cacciatore et al., 2018; Lee et al., 2022; Sakya et al., 2021; Shehata & Strömbäck, 2021) as well as on people's ability to detect misinformation (e.g., Diehl & Lee, 2022; Tandoc et al., 2021), the mechanisms that may help explain such relationships remain underexplored, especially in the context of health/-science knowledge acquisition. Thus, in this study, we proposed and tested two potential mechanisms that may explain the link between social media news use and knowledge about COVID-19: NFMP and information overload. Specifically, we hypothesized that NFMP mediates the link, consistent with studies that found social media use increases NFMP, which negatively affects political knowledge gain (e.g., Lee, 2020). Since individuals may vary in their level of NFMP, we also tested the moderating effect of information overload when it comes to the effect of social media news use on NFMP. We found that our proposed model is supported by the panel data.

First, social media news consumption made people both uninformed and misinformed about COVID-19. To be more precise, while the indirect pathways proposed in the model turned out to be significant for both outcome variables (i.e., factual knowledge gain and misinformation detection), the direct path between social media news consumption and factual knowledge gain failed to reach significance. This is unsurprising, as research shows that news consumption via online platforms may not have a direct effect on health knowledge gains (Lee et al., 2016; Lee & Ho, 2015). Complicating this is the mainstreaming of COVID-19 misinformation as social media platforms amplify false and misleading narratives propagated by individuals and conspiracy groups that took advantage of the wide reach of these platforms (Viswanath et al., 2020). Future studies can further explore similarities and differences between factual knowledge and the ability to detect misinformation.

Second, we found support for previous findings that showed using social media for COVID-19 news leads to NFMP (Lee, 2020; Song et al., 2016). Those who seek news on social media tend to report higher levels of NFMP. Third, while most studies have examined the impact of NFMP on factual *political* knowledge (Gil de Zuniga et al., 2017; Lee, 2020), we sought to expand on this work by examining its impact on COVID-19 related knowledge as well as misinformation. We found that even within the specific context of the COVID-19, NFMP has a negative relationship with factual knowledge. We also sought to advance our understanding of health/science-related knowledge by also testing the impact of NFMP on what we propose as another type of health/science-related knowledge, which is the ability to detect COVID-19- related misinformation. Indeed, NFMP also showed negative effects on misinformation detection.

Fourth, we also explored the moderating role of information overload, as not all social media users display high NFMP. Information overload has been examined in the context of health communication, which individuals may experience when seeking information about health concerns and conditions, such as cancer (Khaleel et al., 2020). However, not many studies have explored whether it may lead users to engage in passive information behavior, expecting important information to reach them even without actively seeking it. This is what we found in this study. Social media news use exerts positive effects on NFMP but more so among those who experience information overload.

These findings show the theoretical utility of NFMP beyond the study

Table 3
Fornell-larcker criterion for discriminant validity.

	CN (W1)	IO (W1)	SMN (W1)	NFMP (W1)	CMD (W1)	SMN (W2)	IO (W2)	NFMP (W2)	CMD (W2)	CN (W2)
CN (W1)	**.68**									
IO (W1)	−.14	**.91**								
SMN (W1)	−.30	.28	**.86**							
NFMP (W1)	−.32	.35	.55	**.76**						
CMD (W1)	.35	−.19	−.37	−.41	**.73**					
SMN (W2)	−.29	.27	.87	.53	−.37	**.87**				
IO (W2)	−.17	.58	.29	.34	−.20	.28	**.92**			
NFMP (W2)	−.34	.33	.54	.70	−.42	.53	.4	**.78**		
CMD (W2)	.38	−.18	−.37	−.42	.70	−.39	−.22	−.43	**.79**	
CN (W2)	.45	−.09	−.27	−.36	.30	−.25	−.16	−.33	.39	**.72**

Table 4
HTMT ratios of discriminant validity.

	CN (W1)	IO (W1)	SMN (W1)	NFMP (W1)	CMD (W1)	SMN (W2)	IO (W2)	NFMP (W2)	CMD (W2)
IO (W1)	.22								
SMN (W1)	.48	.32							
NFMP (W1)	.54	.41	.62						
CMD (W1)	.58	.22	.42	.50					
SMN (W2)	.47	.29	.95	.59	.42				
IO (W2)	.28	.64	.32	.39	.23	.31			
NFMP (W2)	.58	.38	.62	.86	.51	.61	.47		
CMD (W2)	.62	.2	.42	.50	.82	.44	.24	.52	
CN (W2)	.94	.14	.38	.53	.44	.35	.23	.51	.56

Table 5
Structural model assessment.

	R^2	Adj R^2	Q^2 predict
Social media news (W2)	.77	.76	.76
Information overload (W2)	.38	.33	.33
NFMP (W2)	.56	.54	.55
COVID misinformation detection (W2)	.54	.51	.51
COVID knowledge (W2)	.33	.27	.22

of political knowledge acquisition. Future studies exploring the impact of social media use on health/science knowledge may also account for the information-acquisition perception that such use may rise among users over time. The perception that one will get important information despite not actively seeking it may also be true when it comes to health/science-related information. As more and more individuals spend their time on social media, they may also be developing the perception that staying on social media will keep them informed, not only on the news but also on other types of information, such as topics related to health and science, even if they do not routinely seek such information. In an era when scientists and health care professionals are being encouraged to increase their presence on social media to reach the public, we must do so with care as there is a potential drawback. While social media platforms have an extensive reach, their affordances and current social purpose may not make them the ideal channels to inform the public. For example, while messages on social media appeal to those with low levels of health literacy because these messages tend to be short, simple, and conversational (Harnett, 2020), they may be low in reliability and may cause information overload (Moorhead et al., 2013). The perceived abundance of health/science information on social media could also increase the faulty perception among social media users (especially among those feeling an information overload on social media) that one

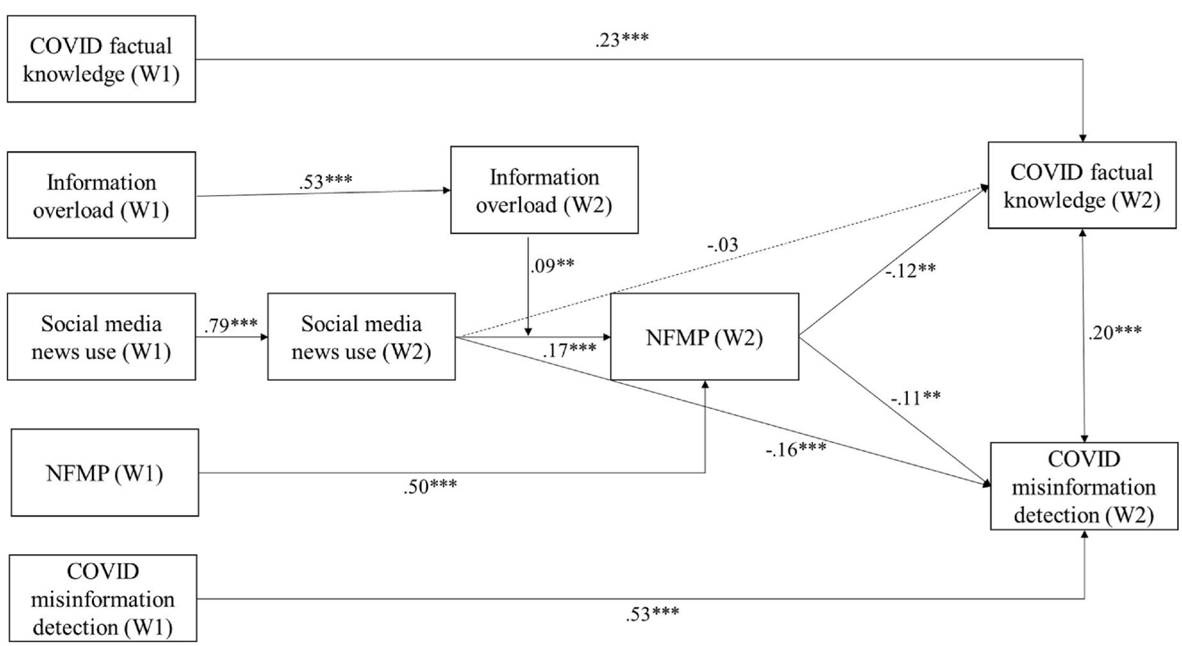

Fig. 2. Results of the PLS-SEM model.

Table 6
Indirect effects of social media news use on COVID knowledge and COVID misinformation detection through the NFMP at the specific values of the moderator.

Mediator	Moderator	DV: COVID factual knowledge			DV: COVID misinformation detection		
NFMP	Information overload	b	SE	95% CI	b	SE	95% CI
	Low	−.01	.01	[-.037,.006]	−.009	.01	[-.032,-.006]
	Middle	−.021	.01	[-.045,-.007]	−.019	.01	[-.04,-.007]
	High	−.033	.01	[-.058,-.013]	−.03	.01	[-.053,-.012]

Note. Entries are unstandardized regression coefficients. We used one standard deviation below the mean, at the mean, and one standard deviation above the mean of information overload on social media to estimate conditional indirect effects at low, middle, and high values of information overload on social media, respectively.

may be sufficiently informed about health/science topics, even without actively trying to stay informed or consulting authoritative sources. Thus, future studies should examine how we can promote health/-science literacy on social media without triggering these potential drawbacks. For example, scientists and health experts should be trained in how to effectively communicate their research and advice on social media channels.

These findings also add to the growing evidence on the negative effects of social media news use on the extent to which users are informed and misinformed. Such negative impact is even more salient when it comes to health/science-related knowledge and within the context of a pandemic. We also sought to examine what mechanisms facilitate the negative impact of social media news use on factual knowledge and misinformation detection when it comes to COVID-19. First, we found that information overload due to social media news use is an important mechanism. Indeed, social media platforms can expose users not only to vast amounts of COVID-19 information but also to pieces of misinformation (Al-Zaman, 2021). Second, we also found that information overload can amplify the effect of NFMP on our outcome variables. This is consistent with what Liu et al. (2021) found, that information overload on social media was positively associated with both social media fatigue and fear of COVID-19 information. However, when individuals believe that important COVID-19 information will come to them even if they do not actively seek it, they then have less control over the quality and accuracy of the information that eventually reaches them, which might explain why NFMP leads to lower factual knowledge and ability to detect COVID-19 misinformation.

There are several practical implications that could be derived from the results of this study. First, while many public health agencies and governments have turned to social media in disseminating timely COVID-19 information due to their mass outreach potential, it is important that only select key messages are communicated succinctly in order to avoid overwhelming the public, which will backfire and leaving people with lower knowledge and misinformed. To do so, health organizations and public health agencies could leverage public social media posts and web-search queries to understand the external information environment and compare how public social media posts differ from private searches on search engines (i.e., Google Trends) to identify information gaps and prioritize key messaging efforts (Lee et al., 2021).

Second, our study shows that social media use is positively associated with NFMP, and the implicit assumption is that social media users perceive that important news would be routed to them automatically through algorithms in social media platforms. There is a need for a concerted effort by government agencies and tech companies to raise digital literacy and equip the public the skills to actively seek out credible COVID-19 information on official websites and verify claims circulating on social media. This is especially important as COVID-19 misinformation disproportionately affects people from lower socioeconomic positions, as well as racial and ethnic minorities. It is important to adopt the lens of equity in COVID-19 communication to avoid the widening of health disparities (Viswanath et al., 2020).

The findings of this study must be examined in the context of several limitations. First, our findings did not hold with the fixed-effects approach. While this approach has its own disadvantages (e.g., the possibility of inflating error variances; Cohen & Cohen, 1983) compared to the autoregressive approach, it is generally considered methodologically more stringent. Given that our findings based on the autoregressive approach can be affected by Simpson's Paradox (Blyth, 1972), in which results from the aggregate data may differ from those based on the individual-level data, they should be interpreted in light of these limitations.

Second, guided by existing NFMP research, we found two potential mechanisms that may explain the negative impact of social media on knowledge about COVID-19. Yet, there are other potential factors that may moderate or mediate the relationship between social media news use and COVID-19 knowledge. For example, there has been a lot of work on the importance of health/science literacy, especially when a lot of health/science-related information is accessible online. Future studies should examine whether health/science literacy and other factors may moderate the negative effects of social media news use on health/science knowledge.

Third, our study extended traditional operationalization of knowledge (e.g., factual knowledge) by also measuring misinformation detection—however, both our measures for factual knowledge and misinformation detection focused on the specific context of COVID-19. Future studies should replicate our study in other topical domains to test the applicability of the proposed framework in this study.

Another limitation of our study lies in our measurement of social media news use. While our measurement of news consumption on social media focuses on active/purposeful news seeking on the platform, not all social media news consumption is purposeful. In fact, a large proportion of news consumption on social media is incidental (Pew, 2014). And conceptually, heavy incidental news exposure on social media can also produce NFMP. Thus, to get the full picture of the relationship between social media news, NFMP, and knowledge, future studies could capture two types of news exposure – purposeful and incidental (e.g., Lee, 2018). Relatedly, our current measure of social media news does not capture where social media news originates. Social media news sources vary a lot, and the quality of news on social media could also vary depending on the source that people choose to follow. By simply asking how frequently respondents consume news on "social media," we cannot really know where this news is coming from and what kind of content they are consuming on social media. Depending on the source and content of COVID-19-related news, the proposed relationship between social media news use and the outcome variables may not be so simple. Future research should be more sensitive to the social media sources of consumed news.

Finally, consistent with the previous literature, we measured NFMP as a general perception. However, NFMP may also be issue-specific. An individual may develop NFMP for general news but may also actively seek news about a particular topic, such as business news (e.g., an individual who buys stocks). Given such a possibility, we acknowledge that the link between social media news seeking and NFMP would have been more precise if we had measured "NFMP on COVID-19-related issues" (rather than general NFMP). However, we still believe that this does not fundamentally threaten the validity of our research as NFMP is a perception produced by the unique technological affordances of social media, which facilitates news exposure, even when not actively seeking information (rather than a perception produced by the specific content of an issue). Thus, general NFMP will likely hold across different issues. Yet, to be more precise, future studies can test whether NFMP could also be issue-specific.

Credit author statement

Sangwon Lee: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data Curation, Writing- Original draft, Writing- Reviewing and Editing, Visualization, Supervision, Project administration, **Edson C. Tandoc Jr:** Conceptualization, Writing- Original draft, Writing- Review & Editing, **Edmund W. J. Lee:** Conceptualization, Writing- Original draft, Writing- Review & Editing.

Data availability

Data will be made available on request.

Appendix A

	Initial W1 sample	Final W1 sample
Age	50.08	54.34
Gender (female)	51.4%	51.3%
Education	Median = 5	Median = 5
Race (White)	71.5%	73.5%
Income	Median = 7	Median = 8
Party affiliation (Republican)	34.3%	34.4%
Print news	2.27	2.22
Radio news	2.28	2.18
TV news	3.12	3.09
Online news	2.86	2.82
Social media news	1.95	1.69
NFMP	2.83	2.67
Information overload	3.08	3.02
COVID factual knowledge	2.20	2.36
COVID misinformation detection	2.58	2.47

Comparison between the initial W1 sample and the final W1 sample.
Note. The final W1 sample only includes the respondents who have also completed the survey at W2.

Appendix B

Latent Variable Correlations

	CN (W1)	IO (W1)	SMN (W1)	NFMP (W1)	CMD (W1)	SMN (W2)	IO (W2)	NFMP (W2)	CMD (W2)
IO (W1)	−.14***								
SMN (W1)	−.31***	.28***							
NFMP (W1)	−.33***	.35***	.55***						
CMD (W1)	.36***	−.19***	−.37***	−.41***					
SMN (W2)	−.30***	.27***	.87***	.53***	−.37***				
IO (W2)	−.17***	.58***	.29***	.34***	−.20***	.28***			
NFMP (W2)	−.34***	.33***	0.54***	.70***	−.42***	.53***	.4***		
CMD (W2)	.38***	−.18***	−.37***	−.42***	.70***	−.39***	−.22***	−.43***	
CN (W2)	.45***	−.09**	−.27***	−.36***	.3***	−.25***	−.16***	−.33***	.39***

Note. *$p < .05$; **$p < .01$; ***$p < .001$.

Appendix C

Scale items

Factual knowledge (Wave 1).
Please choose the statement that is CORRECT about COVID-19.

a. Coronavirus is no worse than the seasonal flu.
b. The virus can only be spread through the air, when people cough or sneeze
c. COVID-19 can be transmitted from pets.
d. You can get both the flu and Covid-19 at the same time
e. Not Sure/Don't know

Which country has the highest number of COVID-19 deaths in the world?

a. Brazil
b. China
c. USA
d. India
e. Not sure/Don't know

Please choose the statement that is INCORRECT about COVID-19.

a. As of September 24, 2020, confirmed virus cases in the United States surpass 6 million.
b. Face masks always protect against coronavirus.
c. There are at least two states which surpassed 10,000 new COVID-19 cases in a single day
d. According to Journalist Bob Woodward's latest book, "Rage," Donald Trump admitted to playing down the seriousness of the COVID-19 pandemic.
e. Not sure/Don't know

Please choose the statement that is CORRECT about COVID-19.

a. According to the CDC, if you've had coronavirus, you don't need a mask.

b. No politician has died from COVID-19 yet.
c. COVID-19 and the flu are caused by the same virus.
d. A vaccine to prevent COVID-19 is currently not available
e. Not sure/Don't know

Factual knowledge (Wave 2).

Which of the following statements is not true, or INCORRECT?

a) President Donald Trump argues that COVID-19 infections are spiking because the U.S. tests extensively
b) President Donald Trump accuses media and Democrats of exaggerating COVID-19 threat
c) After President Donald Trump returned to the White House after being hospitalized for COVID-19, he has been holding rallies without social distancing
d) WHO officially recommended lockdowns as the primary strategy to control the COVID-19
e) Not sure/Don't know

During the final presidential debate, President Donald Trump said, this state has been like a prison during the coronavirus pandemic, because the governor has kept this state closed. Which state is it?

a) Pennsylvania
b) Michigan
c) Wisconsin
d) Florida
e) Not sure/Don't know

According to the official U.S. death count, how many people approximately have died of Covid-19 so far in the U.S? (as of 2020 presidential election date).

a) Less than 50,000
b) 50,000-less than 100,000
c) 100,000–500,000
d) More than 500,000
e) Not sure/Don't know

Which of the following statements is not true, or INCORRECT?

a) President Donald Trump has been calling the coronavirus the 'Chinese Virus'
b) After three days in the hospital, President Donald Trump returned to the White House wearing a face mask
c) Joe Biden said President Donald Trump is responsible for contracting coronavirus,
d) During the 2020 presidential election campaign, President Donald Trump has attacked and denigrated Dr. Anthony Fauci (the director of the National Institute of Allergy and Infectious Diseases)
e) Not sure/Don't know

Misinformation Items (Wave 1).

Statements	Correct	Incorrect	Don't know
The malaria drug Hydroxychloroquine is an effective treatment for COVID-19.	52%	24.3%	27.7%
COVID-19 originated from a biowarfare lab in Wuhan, China.	31.5%	39.0%	29.5%
Children are "virtually immune" to COVID-19.	56.3%	20.8%	23.0%
Most people who get COVID–19 will have a mild form of the illness and recover without needing professional medical care. (True story)	47.7%	27.5%	24.9%
Injecting or consuming bleach or disinfectant kills the virus.	70.6%	12.5%	16.9%
Postal packages and envelopes can spread the COVID-19 virus.	40.7%	23.1%	36.2%
The CDC admitted that only 6% of deaths counted toward the pandemic totals were from COVID-19.	33.4%	27.4%	39.1%
There is direct evidence that Vitamin D Protect Against COVID-19.	36.3%	25.6%	38.2%
99% of COVID-19 cases are "totally harmless."	48.6%	25.2%	26.1%

Misinformation Items (Wave 2).

Statements	Correct	Incorrect	Don't know
The recent spike in US coronavirus cases is solely caused by an increase in testing.	50.5%	25.8%	23.6%
President Donald Trump now has immunity from COVID-19.	46.8%	21.3%	30.9%
Dr. Anthony Fauci told CNN in October that the U.S. is "rounding the corner" on COVID-19.	52.3%	15.2%	32.5%
The World Health Organization (WHO) changed its position and admitted that Donald Trump was right about lockdowns.	49.5%	14.8%	25.7%

(*continued on next page*)

(*continued*)

Statements	Correct	Incorrect	Don't know
Dr. Anthony Fauci wrote a paper blaming 1918–19 flu deaths on masks.	48.9%	12.3%	38.8%
President Donald Trump said "The doctors said they've never seen a body kill the Coronavirus like my body. They tested my DNA and it wasn't DNA. It was USA.	39.7%	24.5%	35.7%
The U.S. has the highest number of COVID-19 deaths in the world. (True story)	57.0%	14.8%	28.3%
COVID-19 cases are rising in only red (Republican) states.	56.8%	14.5%	28.7%

NFMP.

How much do you agree or disagree with each of the following statements about your own experience with news?

I rely on my friends to tell me what's important when news happens.

I can be well informed even when I don't actively follow the news.

I don't worry about keeping up with the news because I know news will find me.

I rely on information from my friends based on what they like or follow through on social media.

I do not worry about keeping up with news because I know news will find me.

I do not have to actively seek news because when important public affairs break, they will get to me on social media.

Response options: Strongly disagree (1) to Strongly agree (5).

Information overload on social media.

How much do you agree or disagree with each of the following statements about your personal experience with social media use? When I am on social media …

I feel overloaded with the amount of information I see.

I am overwhelmed by how much content there is.

I receive more information than I can process.

Response options: Strongly disagree (1) to Strongly agree (5).

Appendix D

Structural Model Assessment of the Fixed Effects PLS-SEM

	R^2	Adj R^2	Q^2 predict
COVID misinformation detection	.01	.00	−.01
COVID knowledge	.01	−.00	−.02
NFMP	.03	.02	−.02

RUNNING HEAD: SOCIAL MEDIA AND COVID-19 KNOWLEDGE 1.

SOCIAL MEDIA AND COVID-19 KNOWLEDGE.

References

Al-Zaman, M. S. (2021). COVID-19-related social media fake news in India. *Journalism and Media, 2*(1), 100–114. https://doi.org/10.3390/journalmedia2010007

Bawden, D., & Robinson, L. (2020). Information overload: An introduction. In *Oxford research encyclopedia of politics*. Oxford University Press.

Blyth, C. R. (1972). On Simpson's paradox and the sure-thing principle. *Journal of the American Statistical Association, 67*(338), 364–366.

Boulos, M. N., & Geraghty, E. M. (2020). Geographical tracking and mapping of coronavirus disease COVID-19/severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) epidemic and associated events around the world: how 21st century GIS technologies are supporting the global fight against outbreaks and epidemics. *International Journal of Health Geographics, 19*(1), 1–12. https://doi.org/10.1186/s12942-020-00202-8

Cacciatore, M. A., Yeo, S. K., Scheufele, D. A., Xenos, M. A., Brossard, D., & Corley, E. A. (2018). Is Facebook making us dumber? Exploring social media use as a predictor of political knowledge. *Journalism & Mass Communication Quarterly, 95*(2), 404–424. https://doi.org/10.1177/1077699018770447

Calvillo, D. P., Ross, B. J., Garcia, R. J., Smelter, T. J., & Rutchick, A. M. (2020). Political ideology predicts perceptions of the threat of covid-19 (and susceptibility to fake news about it). *Social Psychological and Personality Science, 11*(8), 1119–1128. https://doi.org/10.1177/1948550620940539

Cha, M., Cha, C., Singh, K., Lima, G., Ahn, Y. Y., Kulshrestha, J., & Varol, O. (2021). Prevalence of misinformation and factchecks on the COVID-19 pandemic in 35 countries: Observational infodemiology study. *JMIR Human Factors, 8*(1), Article e23279. https://doi.org/10.2196/23279

Cinelli, M., Quattrociocchi, W., Galeazzi, A., Valensise, C. M., Brugnoli, E., Schmidt, A. L., Zola, P., Zollo, F., & Scala, A. (2020). The COVID-19 social media infodemic. *Scientific Reports, 10*(1), 1–10. https://doi.org/10.1038/s41598-020-73510-5

Cohen, J., & Cohen, P. (1983). *Applied multiple regression/con elation analysis for the behavioral sciences*. Hillsdale, NJ: Erlbaum.

Diddi, P., & Lundy, L. K. (2017). Organizational twitter use: Content analysis of tweets during breast cancer awareness month. *Journal of Health Communication, 22*(3), 243–253. https://doi.org/10.1080/10810730.2016.1266716

Diehl, T., & Lee, S. (2022). Testing the cognitive involvement hypothesis on social media: 'News finds me' perceptions, partisanship, and fake news credibility. *Computers in Human Behavior, 128*. https://doi.org/10.1016/j.chb.2021.107121

Eckert, S., Sopory, P., Day, A., Wilkins, L., Padgett, D., Novak, J., … Gamhewage, G. (2018). Health-related disaster communication and social media: Mixed-method systematic review. *Health Communication, 33*(12), 1389–1400. https://doi.org/10.1080/10410236.2017.1351278

Eveland, W. P., Jr., Hayes, A. F., Shah, D. V., & Kwak, N. (2005). Understanding the relationship between communication and political knowledge: A model comparison approach using panel data. *Political Communication, 22*(4), 423–446. https://doi.org/10.1080/10584600500311345

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research, 18*(3), 382–388.

Gil de Zúñiga, H., Weeks, B., & Ardèvol-Abreu, A. (2017). Effects of the news-finds-me perception in communication: Social media use implications for news seeking and learning about politics. *Journal of Computer-Mediated Communication, 22*(3), 105–123. https://doi.org/10.1111/jcc4.12185

Granderath, J. S., Sondermann, C., Martin, A., & Merkt, M. (2020). Actual and perceived knowledge about COVID-19: The role of information behavior in media. *Frontiers in Psychology, 12*. https://doi.org/10.3389/fpsyg.2021.778886

Hair, J. F. (2010). *Multivariate data analysis: A global perspective*. Upper Saddle River, N.J: Pearson.

Hair, J. F., Jr., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: Updated guidelines on which method to use. *International Journal of Multivariate Data Analysis, 1*(2), 107–123.

Harnett, S. (2020). Health literacy, social media and pandemic planning. *Journal of Consumer Health on the Internet, 24*(2), 157–162. https://doi.org/10.1080/15398285.2020.1756677

Hart, P. S., Chinn, S., & Soroka, S. (2020). Politicization and polarization in COVID-19 news coverage. *Science Communication, 42*(5), 679–697.

Henseler, J., & Chin, W. W. (2010). A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling. *Structural Equation Modeling, 17*(1), 82–109.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135.

Hong, H., & Kim, H. J. (2020). Antecedents and consequences of information overload in the covid-19 pandemic. *International Journal of Environmental Research and Public Health, 17*(24), 1–15. https://doi.org/10.3390/ijerph17249305

Hswen, Y., Xu, X., Hing, A., Hawkins, J. B., Brownstein, J. S., & Gee, G. C. (2021). Association of "#covid19" versus "#chinesevirus" with anti-asian sentiments on twitter: March 9–23, 2020. *American Journal of Public Health, 111*(5), 956–964. https://doi.org/10.2105/ajph.2021.306154

Jensen, J. D., Liu, M., Carcioppolo, N., John, K. K., Krakow, M., & Sun, Y. (2017). Health information seeking and scanning among US adults aged 50–75 years: Testing a key postulate of the information overload model. *Health Informatics Journal, 23*(2), 96–108. https://doi.org/10.1177/1460458215627290

Khaleel, I., Wimmer, B. C., Peterson, G. M., Zaidi, S. T. R., Roehrer, E., Cummings, E., & Lee, K. (2020). Health information overload among health consumers: A scoping review. *Patient Education and Counseling, 103*(1), 15–32. https://doi.org/10.1016/j.pec.2019.08.008

Kim, H. K., & Tandoc, E. C., Jr. (2021). Wear or not to wear a mask? Recommendation inconsistency. *Health Communication*, 1–9. https://doi.org/10.1080/10410236.2020.1871170. Government Trust and the Adoption of Protection Behaviors in Cross-Lagged TPB Models.

Lee, S. (2018). The role of social media in protest participation: The case of candlelight vigils in South Korea. *International Journal of Communication, 12*, 1523–1540.

Lee, S. (2020). Probing the mechanisms through which social media erodes political knowledge: The role of the news-finds-me perception. *Mass Communication and Society, 23*(6), 810–832. https://doi.org/10.1080/15205436.2020.1821381

Kuklinski, J, Quirk, P, Jerit, J, Schwieder, D, Rich, R, et al. (2000). Misinformation and the currency of democratic citizenship. *The Journal of Politics, 62*(3), 790–816.

Lee, E. W. J., Bekalu, M. A., Mccloud, R. F., & Viswanath, K. (2021). Toward an extended infodemiology framework : Leveraging social media data and web search queries as digital pulse on cancer communication. *Health Communication*, 1–14. https://doi.org/10.1080/10410236.2021.1951957

Lee, S., Diehl, T., & Valenzuela, S. (2022). Rethinking the virtuous circle hypothesis on social media: Subjective versus objective knowledge and political participation. *Human Communication Research, 48*(1), 57–87. https://doi.org/10.1093/hcr/hqab014

Lee, E. W. J., & Ho, S. S. (2015). The perceived familiarity gap hypothesis: Examining how media attention and reflective integration relate to perceived familiarity with nanotechnology in Singapore. *Journal of Nanoparticle Research, 17*(228), 1–15. https://doi.org/10.1007/s11051-015-3036-z

Lee, E. W. J., Shin, M., Kawaja, A., & Ho, S. S. (2016). The augmented cognitive mediation model: Examining antecedents of factual and structural breast cancer knowledge among Singaporean women. *Journal of Health Communication, 21*(5), 583–592. https://doi.org/10.1080/10810730.2015.1114053

Lee, S., & Xenos, M. (2019). Social distraction? Social media use and political knowledge in two US presidential elections. *Computers in Human Behavior, 90*, 18–25. https://doi.org/10.1016/j.chb.2018.08.006

Lee, E. W. J., & Yee, A. Z. H. (2020). Toward data sense-making in digital health communication research: Why theory matters in the age of big data. *Frontiers in Communication, 5*(11), 1–10. https://doi.org/10.3389/fcomm.2020.00011

Liu, H., Liu, W., Yoganathan, V., & Osburg, V. S. (2021). COVID-19 information overload and generation Z's social media discontinuance intention during the pandemic lockdown. *Technological Forecasting and Social Change, 166*(August 2020), Article 120600. https://doi.org/10.1016/j.techfore.2021.120600

Mian, A., & Khan, S. (2020). Coronavirus: The spread of misinformation. *BMC Medicine, 18*(89), 1–2. https://doi.org/10.1186/s12916-020-01556-3

Mohammed, M., Sha'aban, A., Jatau, A. I., Yunusa, I., Isa, A. M., Wada, A. S., … Ibrahim, B. (2021). Assessment of COVID-19 information overload among the general public. *Journal of Racial and Ethnic Health Disparities*, 1–9. https://doi.org/10.1007/s40615-020-00942-0

Moorhead, S., Hazlett, D., Harrison, L., Carroll, J., Irwin, A., & Hoving, C. (2013). A new dimension of health care: Systematic review of the uses, benefits, and limitations of social media for health communication. *Journal of Medical Internet Research, 15*(4), 1–17. https://doi.org/10.2196/jmir.1933

Park, C. S., & Kaye, B. K. (2020). What's this? Incidental exposure to news on social media, news-finds-me perception, news efficacy, and news consumption. *Mass Communication and Society, 23*(2), 157–180. https://doi.org/10.1080/15205436.2019.1702216

Pennycook, G., McPhetres, J., Zhang, Y., Lu, J. G., & Rand, D. G. (2020). Fighting COVID-19 misinformation on social media: Experimental evidence for a scalable accuracy-nudge intervention. *Psychological Science, 31*(7), 770–780. https://doi.org/10.1177/0956797620939054

Pew. (2014). *8 key takeaways about social media and news*. https://www.journalism.org/2014/03/26/8-key-takeaways-about-social-media-and-news/.

Pew. (2018). *News use across social media platforms 2018*. https://www.journalism.org/2018/09/10/news-use-across-social-media-platforms-2018/.

Pew. (2021). *More than eight-in-ten Americans get news from digital devices*. https://www.pewresearch.org/fact-tank/2021/01/12/more-than-eight-in-ten-americans-get-news-from-digital-devices/.

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology, 63*(1), 539–569.

Sakya, S. M., Scoy, L. J. V., Garman, J. C., Miller, E. L., Snyder, B., Wasserman, E., … Lennon, R. P. (2021). The impact of COVID-19-related changes in media consumption on public knowledge: Results of a cross-sectional survey of Pennsylvania adults. *Current Medical Research and Opinion, 37*(6), 911–915. https://doi.org/10.1080/03007995.2021.1901679

Scheufele, D. A., & Krause, N. M. (2019). Science audiences, misinformation, and fake news. *Proceedings of the National Academy of Sciences, USA, 116*, 7662–7669. https://doi.org/10.1073/pnas.1805871115

Shah, D. V., Cho, J., Eveland, W. P., Jr., & Kwak, N. (2005). Information and expression in a digital age: Modeling Internet effects on civic participation. *Communication Research, 32*(5), 531–565. https://doi.org/10.1177/0093650205279209

Shehata, A., & Strömbäck, J. (2021). Learning political news from social media: Network media logic and current affairs news learning in a high-choice media environment. *Communication Research, 48*(1), 125–147. https://doi.org/10.1177/0093650217749354

Song, H., Gil de Zúñiga, H., & Boomgaarden, H. G. (2020). Social media news use and political cynicism: Differential pathways through "news finds me" perception. *Mass Communication and Society, 23*(1), 47–70. https://doi.org/10.1080/15205436.2019.1651867

Song, H., Jung, J., & Kim, Y. (2016). Perceived news overload and its cognitive and attitudinal consequences for news usage in South Korea. *Journalism & Mass Communication Quarterly, 94*(4), 1172–1190. https://doi.org/10.1177/1077699016679975

Strekalova, Y. A., & Krieger, J. L. (2017). Beyond words: Amplification of cancer risk communication on social media. *Journal of Health Communication, 22*(10), 849–857. https://doi.org/10.1080/10810730.2017.1367336

Tandoc, E. C., Lee, J., Chew, M., Tan, F. X., & Goh, Z. H. (2021). Falling for fake news: The role of political bias and cognitive ability. *Asian Journal of Communication, 31*(4), 237–253. https://doi.org/10.1080/01292986.2021.1941149

Uscinski, J. E., Enders, A. M., Klofstad, C. A., Seelig, M. I., Funchion, J. R., Everett, C., … Murthi, M. N. (2020). Why do people believe COVID-19 conspiracy theories? *Harvard Kennedy School Misinformation Review, 1*(3). https://doi.org/10.37016/mr-2020-015

Van Stee, S. K., & Yang, Q (2018). Online cancer information seeking: Applying and extending the comprehensive model of information seeking. *Health Communication, 33*(12), 1583–1592. https://doi.org/10.1080/10410236.2017.1384350

Viswanath, K., Lee, E. W., & Pinnamaneni, R. (2020). We need the lens of equity in COVID-19 communication. *Health Communication, 35*(14), 1743–1746. https://doi.org/10.1080/10410236.2020.1837445

Vos, S. C., & Buckner, M. M. (2016). Social media messages in an emerging health crisis: Tweeting bird flu. *Journal of Health Communication, 21*(3), 301–308. https://doi.org/10.1080/10810730.2015.1064495

Vosoughi, S., Roy, D., & Aral, S. (2018). The spread of true and false news online. *Science, 359*, 1146–1151. https://doi.org/10.1126/science.aap9559

Watson, N., & Wooden, M. (2006). Modelling longitudinal survey response: The experience of the HILDA survey. In *ACSPRI social science methodology conference* (pp. 10–13). Sydney, Australia. Retrieved from http://old.acspri.org.au/conference2006/proceedings.

Zhang, L., Xu, L., & Zhang, W. (2017). Social media as amplification station: Factors that influence the speed of online public response to health emergencies. *Asian Journal of Communication, 27*(3), 322–338. https://doi.org/10.1080/01292986.2017.1290124