

# Who Is Susceptible to Online Health Misinformation? A Test of Four Psychosocial Hypotheses

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**Objective:** Health misinformation on social media threatens public health. One question that could lend insight into how and through whom misinformation spreads is whether certain people are susceptible to many types of health misinformation, regardless of the health topic at hand. This study provided an initial answer to this question and also tested four hypotheses concerning the psychosocial attributes of people who are susceptible to health misinformation: (1) deficits in knowledge or skill, (2) preexisting attitudes, (3) trust in health care and/or science, and (4) cognitive miserliness. **Method:** Participants in a national U.S. survey ( $N = 923$ ) rated the perceived accuracy and influence of true and false social media posts about statin medications, cancer treatment, and the Human Papilloma Virus (HPV) vaccine and then responded to individual difference and demographic questions. **Results:** Perceived accuracy of health misinformation was strongly correlated across statins, cancer, and the HPV vaccine ( $r_s \geq .70$ ), indicating that individuals who are susceptible to misinformation about one of these topics are very likely to believe misinformation about the other topics as well. Misinformation susceptibility across all three topics was most strongly predicted by lower educational attainment and health literacy, distrust in the health care system, and positive attitudes toward alternative medicine. **Conclusions:** A person who is susceptible to online misinformation about one health topic may be susceptible to many types of health misinformation. Individuals who were more susceptible to health misinformation had less education and health literacy, less health care trust, and more positive attitudes toward alternative medicine.


**Keywords:** misinformation, vaccination, cancer treatment, statins, social media


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Health misinformation—described recently in the *Journal of the American Medical Association* as a claim of fact that is false due to lack of evidence (Chou et al., 2018)—is pervasive and threatens public health. It impedes the delivery of evidence-based medicine and negatively affects the quality of patient-clinician relationships by making patients skeptical of guidelines and recommendations (Hill et al., 2019; Jolley & Douglas, 2014). The Internet has

allowed unprecedented access to both accurate and inaccurate health information. Online social media platforms can increase people's exposure to false information by creating incidental exposure to content shared by other users, as well as uncritical and self-reinforcing conversations where false information is shared (Del Vicario et al., 2016). Misinformation can spread farther and faster on social media compared to similar true content (Vosoughi et al.,

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2018). As people increasingly turn to social media for health information, support, and advice (Rutten et al., 2006), reducing misinformation has become a global public health imperative.

In response to concerns about the spread of health misinformation online, technology companies and health experts have been spurred to action. Google has altered its search engine algorithm to prioritize reputable health websites (Shaban, 2018), and Facebook has made vaccine misinformation more difficult to find on their platform (Bickert, 2019). Research has shown that peer corrections and interventions that increase user awareness of misinformation can be effective at reducing misperceptions following exposure to misinformation (Bode & Vraga, 2015, 2018; Roozenbeek & van der Linden, 2019; Vraga & Bode, 2018). Recent research also indicates that subtly reminding people about accuracy improves people's choices about what COVID-19 information to share online (Pennycook et al., 2020). However, little is currently known about who is most susceptible to health misinformation or why. By "susceptible," we mean a tendency to perceive health misinformation as accurate and make health decisions based on misinformation.

The literature on vaccination attitudes provides some insight on this question, showing that vaccine hesitancy (which is shaped to some extent by misinformation) is related to positive attitudes toward alternative and "natural" medicine (Browne et al., 2015; DiBonaventura & Chapman, 2008), lack of trust (Benin et al., 2006), and lack of knowledge (Downs et al., 2008), among other individual differences (Hornsey et al., 2018). Individuals with these characteristics might be more susceptible to believing health misinformation about vaccines specifically or about health topics more broadly.

Health research often focuses on one health topic at a time, and as a result, it is unclear whether individuals who are susceptible to misinformation in one health context (e.g., vaccines) also tend to be susceptible to other types of health misinformation. Research has highlighted the prevalence of vaccine misinformation online (Brewer et al., 2017; Buchanan & Beckett, 2014; Shah et al., 2019; Wang et al., 2019), but misinformation knows no boundaries and is certainly not limited to vaccination. Cancer treatment and statin medications are other health topics about which a large amount of online misinformation exists (Navar, 2019). While people probably attend to health information (and misinformation) more when it is personally relevant, it is possible that some people are generally susceptible to health misinformation regardless of the particular health topic at hand and whether it is personally relevant or not. Identifying whether susceptibility is generalized in this way—and if so, what psychosocial factors are common to those who are susceptible—could provide important information about how to design more effective health communication interventions and disseminate those interventions more efficiently (Witte et al., 2001).

There are currently four dominant—but not necessarily mutually exclusive—perspectives that have been offered to explain why certain people might be generally more susceptible to misinformation than others (see Table 1), which we draw from the vaccination literature, research on political misinformation, as well as the broader psychological literature (Browne et al., 2015; Dubé et al., 2015; Lewandowsky et al., 2012; Pennycook et al., 2020; Pennycook & Rand, 2020; Scherer & Pennycook, 2020). Research has not yet systematically examined these hypotheses in the context of

online health misinformation (Scherer & Pennycook, 2020). First, the deficit hypothesis proposes that people are susceptible to misinformation because they lack the knowledge, education, and/or reasoning skills required to critically evaluate information. Second, some people may be susceptible to misinformation because they fail to adequately scrutinize information that agrees with their preferred views (a phenomenon referred to broadly as motivated reasoning; Kahan et al., 2012; Kunda, 1990; Stanovich et al., 2013). Hence, certain health-related attitudes—particularly those that tend to align with misinformation messages—might cause an individual to be susceptible to misinformation, even if they possess the skills required to discern fact from fiction. A third hypothesis is that due to historical injustices, perceived economic incentives, or other reasons, people distrust science or the health care system and reject anything they perceive as coming from those sources (Benin et al., 2006; Brewer et al., 2017). A fourth hypothesis is that some people are susceptible to misinformation because they do not think carefully enough about the information they encounter online (Pennycook et al., 2020). That is, it is not necessarily the case that people who believe misinformation are motivated to come to a particular conclusion. Instead, they tend to be cognitive misers, not expending enough mental effort to be able to reliably distinguish between fact and fiction (Pennycook & Rand, 2018).

Given the multitude of perspectives on who is susceptible to misinformation, and the dearth of data addressing them in health contexts, the primary goal of the present research was to answer two research questions:

1. Are some people generally more susceptible to online health misinformation than others, regardless of the particular health topic at hand?

To answer this question, we asked survey respondents to evaluate the accuracy of true and false social media posts on three topics: statins, cancer treatment, and the Human Papilloma Virus (HPV) vaccine. We predicted that misinformation susceptibility for all three topics would be highly correlated; that is, a person who believes misinformation about one health topic will also believe misinformation about the other two topics.

2. What type of person is susceptible to online health misinformation? That is, what are some important psychosocial predictors of misinformation susceptibility?

To answer this question, we assessed predictors of discernment between the true and false social media posts, focusing on psychosocial variables relating to each of the four hypotheses described earlier (see Table 1), as well as demographic and health characteristics.

## Method

This national U.S. online survey was conducted December 2019 to January 2020. Factual and misinformation social media posts were obtained from Facebook and Twitter using the websites' internal search engines. These social media platforms were chosen because they are among the largest in terms of active users (e.g., Facebook reportedly has 2.4 billion users at the time of this writing). Facebook users create a network of friends and can also join

**Table 1**

*Perspectives That Have Been Offered to Explain Why Some People Are More Susceptible to Misinformation, Directional Predictions, Measures Used to Test These Hypotheses in the Present Study, and Measure Characteristics Observed in the Present Study*

Hypothesis	Prediction	Measures	Measure characteristics
Deficit hypothesis	Individuals with less education and/or health literacy will be more susceptible to misinformation.	Education Health literacy (Chew et al., 2008)	$M = 6.83$ , $SD = 1.89$ 1–10 ordinal scale $M = 4.56$ , $SD = 0.65$ , Pearson $r$ between 2 items = .31, $p < .001$ $M = 4.54$ , $SD = 1.11$ , $\alpha = .86$ 1–7 Likert scale, <i>strongly disagree</i> to <i>strongly agree</i>
Health-related attitudes	Individuals who are medical minimizers will be more susceptible to online health misinformation than maximizers because online health misinformation generally persuades people to not follow standard medical advice and to reject allopathic interventions.* Individuals with more positive attitudes toward complementary and alternative medicine (CAM) will be more susceptible to health misinformation than individuals with negative attitudes because online health misinformation often persuades people to not follow standard medical advice.*	Medical Maximizer-Minimizer Scale (Scherer et al., 2016) CAM (Hyland et al., 2003)	CAM subscale: $M = 2.82$ , $SD = 0.83$ , $\alpha = .68$ Holistic health subscale: $M = 4.84$ , $SD = 0.73$ , $\alpha = .78$ 1–6 Likert scale, <i>strongly disagree</i> to <i>strongly agree</i>
Trust	Individuals with more trust in the healthcare system will be less susceptible to online health misinformation.* Individuals who believe in science as the best way of gaining knowledge will be less susceptible to health misinformation.	Trust in the healthcare system (Shea et al., 2008) Belief in science (Farias et al., 2013)	$M = 2.98$ , $SD = 0.71$ , $\alpha = .82$ 1–5 Likert scale, <i>strongly disagree</i> to <i>strongly agree</i> $M = 3.70$ , $SD = 1.18$ , $\alpha = .91$ 1–6 Likert scale, <i>strongly disagree</i> to <i>strongly agree</i>
Cognitive miserliness	Cognitive misers will be more susceptible to health information than those who engage in more reflective thinking.	Cognitive Reflection Test (Frederick, 2005; Pennycook & Rand, 2018)	$M = 2.04$ , $SD = 1.72$ , $\alpha = .71$ 6 questions scored as correct/incorrect

*Note.* The health misinformation that we found on social media tended to reject standard medical recommendations and allopathic treatments, which led to directional predictions indicated by asterisks (\*). However, misinformation from other sources might oversell the benefits of medications and standard interventions. We are restricting our hypotheses to the former type of misinformation, with the latter being a separate question.

topically focused groups where they can connect with strangers who share their interests. On Twitter, users manage the content they see by following other accounts. On both platforms, users share content (e.g., news articles, websites, “meme” graphics, etc.) that appears on the newsfeed of their friends and followers.

All social media posts used in this research were public (i.e., available to anyone). Search terms were informed by 4 months monitoring Facebook groups related to statins, alternative cancer treatments, and vaccination. Search terms included “statins,” “statin harms,” “the facts about statins,” and “statin dangers,”; “cancer treatments,” “alternative cancer treatments,” “the facts about chemotherapy,” and “cancer killing herbs,”; and “HPV vaccine,” “HPV vaccine harms,” “the facts about the HPV vaccine,” “HPV vaccine risks,” and “Gardasil risks.” Authors Jon McPhetres and Laura D. Scherer conducted the searches and collected 52 social media posts preliminarily identified as potential misinformation. These were sent to coauthors Daniel D. Matlock, Larry A. Allen, Allison Kempe, and Christopher E. Knoepke, who rated each post using their expertise in cardiology, pediatrics, and internal medicine as either (a) false/mostly false, (b) true/mostly true, or (c) unable to assess. In making these judgments, we decided through discussion that posts with multiple true and false claims should be identified as mostly false if both true and false information are presented as being equally valid or if true information is presented inappropriately as supporting a false conclusion (we

provide an in-depth discussion of these decisions in the “Discussion” section). A second round of Facebook and Twitter searches identified posts that were potentially true, and these were similarly rated by the study team.

The final social media posts used as stimuli were selected using the following criteria: (a) the post had to make at least one clear claim, (b) the claim(s) had to be identifiable as true/mostly true or false/mostly false (some types of claims, such as personal stories, could not be verified as true or false), and (c) coauthors had to agree that each post was either true/mostly true or false/mostly false. Among posts that met these criteria, preference was given to posts that contained graphics and fewer words to minimize respondent burden. When multiple posts made the same claim, we tried to minimize content repetition; however, due to the abundance of posts claiming that the HPV vaccine increased cervical cancer rates, we allowed two posts of this nature to be included in the final stimuli. A final collection of 24 social media posts, half of which were identified as true/mostly true and half false/mostly false—eight each for statins, cancer, and HPV vaccine—were evaluated a final time by Allison Kempe, Daniel D. Matlock, Larry A. Allen, and Christopher E. Knoepke to confirm agreement on their true/false categorization.

The perceived accuracy of a given social media post might be influenced by social factors such who shares it, how many “likes” it receives, and comments from other social media users.

However, these social cues were not the focus of the present research; instead, we were interested in the perceived accuracy of the claims presented in the social media posts. Hence, this research sought to determine who tends to believe health misinformation that has been shared on social media, holding these external social cues constant. We therefore controlled for the number of likes, shares, and comments that each post had received. This was achieved by dividing the 24 posts into four groups, with one of each type of post per group (statin false, statin true, cancer false, cancer true, vaccine false, vaccine true) and altering the number likes, shares, and comments so that they were identical for all stimuli within a group and similar (but not identical) across groups. All stimuli can be found at <https://osf.io/v9wd4/>.

## Sample

We preregistered a plan to collect a sample size of  $N = 1,000$  participants. We powered this study to detect small correlations between individual difference measures and social media accuracy judgments. A power analysis indicated that this sample size would allow us to detect small correlations ( $r = .12$ ) at 95% power with  $\alpha = .05$ .

Participants were English-speaking members of the general U.S. public who were recruited using Dynata, a private survey company that maintains a panel of millions of individuals across the United States who have agreed to receive solicitations via email to participate in online surveys in exchange for entry into lotteries for modest cash prizes. Although this was not a probability-based sample and therefore cannot claim national representativeness, other research has shown a high degree of overlap between findings from online probability samples and convenience samples in large, national online surveys (Jeong et al., 2019; Mullinix et al., 2015). Participants were invited by means of email with an embedded link. Participation was voluntary, and all responses were anonymous. Participants were U.S. residents age 40–80, 40 being an age at which cancer and heart disease can become salient health concerns, and the maximum age of 80 was chosen to address possible breaches in anonymity in adults at advanced ages. Targeted recruitment of participants in certain demographic categories was used to obtain race and education distributions that approximated U.S. population proportions. The study was approved by the University of Colorado Institutional Review Board.

## Design, Procedure, and Measures

This survey utilized a 3 (Information Type: statins, cancer treatment, HPV vaccine)  $\times$  2 (Information Veracity: true vs. false)  $\times$  2 (Judgment: accuracy vs. likelihood of sharing) within-subjects experimental design. After being introduced to the study, participants rated the perceived accuracy of all 24 social media posts: “To the best of your knowledge, how accurate is the information in this social media post?” with 4 scale points labeled *completely false*, *mostly false*, *mostly true*, and *completely true*. A second question elicited perceived influence of the posts—for example, “If you were prescribed a statin, would this information influence your decision to take it?” with the response scale *definitely not*, *probably not*, *probably yes*, and *definitely yes*. These social media posts were presented in randomized order.

After rating the social media posts, participants completed measures relevant to our hypotheses, which are displayed in Table

1. Table 1 also describes directional predictions. The deficit hypothesis was examined using measures of educational attainment, health literacy (Chew et al., 2008), and the Scientific Reasoning Scale (SRS) subset of five items assessing reasoning about causality, control groups, confounding, random assignment, and double blinding (Drummond & Fischhoff, 2017). Attitudes toward holistic health (HH) and complementary and alternative medicine (CAM; Hyland et al., 2003) and the Medical Maximizer-Minimizer Scale (Scherer et al., 2016) were included as health-related attitudes that frequently align with the messages of online health misinformation. The HH and CAM are two subscales, one that assesses HH attitudes (beliefs that diet, lifestyle, and stress can affect health) and the other that assesses CAM attitudes. A belief in science scale (Farias et al., 2013) and health care system trust scale (Shea et al., 2008) assessed the trust hypothesis. The six-item Cognitive Reflection Test (CRT) was used to assess the tendency toward reflective reasoning versus cognitive miserliness (Frederick, 2005; Pennycook & Rand, 2018). Each of these measures was selected because they have been previously validated (at least to some extent; see citations for each scale) and shown to have acceptable internal reliability in prior research. Although the construct validity of the CRT as a straightforward measure of cognitive reflection has been questioned (Patel et al., 2018), this measure also currently dominates the literature on cognitive reflection and is associated with everyday beliefs and behaviors (Pennycook et al., 2015), including the ability to discern between true and false news content (Pennycook & Rand, 2018), making it a reasonable measure to assess the cognitive miserliness hypothesis.

Participants next reported whether they had the following relevant health experiences: diagnosed with high cholesterol, currently take a statin, or diagnosed with cancer (if yes, what type of cancer). Participants reported whether they are a parent or guardian, if they currently have a child age 10–18, and if so, whether that child has been vaccinated. They also reported the social media platforms they use (if any) and how many days per week and hours per day they engage with social media. Standard demographics were also collected. There were two attention check questions appearing toward the end of the survey and embedded in the belief in science and health care system trust scales. These asked participants to provide a specific response to show that they were reading the questions.

## Analyses

To address Research Question 1, we computed the average of the four accuracy ratings for each type of information, resulting in six summary scores (statins true, statin false, cancer true, cancer false, HPV vaccine true, HPV vaccine false). Next, we computed simple correlations between these six variables, predicting that we would observe positive and moderate-sized (e.g.,  $r = .4$ – $.6$ ) correlations among the three types of false information and among the three types of true information, versus small-to-moderate negative correlations between true and false information within each health context (e.g.,  $r = -.1$  to  $-.3$ ). Using Fisher’s  $r$ -to- $z$  transformation, we then compared the size of correlations across health contexts to the correlations among four ratings within each health context. We also used a mixed-model analysis of variance to compare perceived accuracy across each of the health contexts (within subject). To address Research Question 2, we conducted linear



regression analyses including all psychosocial measures as simultaneous predictors of perceived accuracy and influence of misinformation (with separate models for each outcome and health context), with demographics, social media use, health measures, and judgments of true information as covariates.

Of note, the subset of five SRS items included in this study showed poor reliability ( $\alpha = .30$ ). As a result, we did not include that measure in the analyses reported here. However, for interested readers, we report in the online supplemental materials regression results that include each of the five SRS items individually (online Supplemental Table F).

## Results

Of 1,290 participants who began the survey, 1,020 completed it (79% completion rate). As planned in our preregistration (<https://osf.io/39xtr/>), we removed participants who failed both attention checks ( $N = 91$ ) or who took less than 5 min to complete the survey ( $N = 6$ ), leaving a final analytic data set of  $N = 923$ . Sample characteristics are displayed in Table 2, and reliability and means (standard deviations) for key predictor measures are reported in Table 1. Participants were 40–80 years old, and the vast majority (94%) of participants used social media of some kind (which is higher than the national rate of 72%; Pew Research Center, 2019), for an average of 5 days per week and 30–60 min per day. Ninety-three percent reported having some kind of health insurance, which is similar to the national rate (Kaiser Family Foundation, 2019). Fifty percent had been told by a doctor they have high cholesterol, 34% reported taking a statin, and 14% had been diagnosed with cancer. Sixty-one percent were parents, and 10% had a child aged 10–18. There was an unintentional imbalance in gender (59% were women), whereas race, education, and household income approximated U.S. population distributions.

Table 3 shows mean scores and standard deviations for responses to each type of information. The total number of participants who rated each social media post as completely false, mostly false, mostly true, or completely true can be found in the online supplemental materials. Participants rated true posts as more accurate than false posts,  $F(1, 922) = 780.84, p < .001, \eta_p^2 = .46$ , and although the size of this effect differed by health topic,  $F(2, 921) = 184.23, p < .001, \eta_p^2 = .28$ , the difference between true and false posts was significant at  $p < .001$  for all three health contexts (see Table 3). Further, participants thought they would be more influenced by true than false posts,  $F(1, 922) = 493.53, p < .001, \eta_p^2 = .34$ , and although this effect also differed by health topic,  $p < .001, \eta_p^2 = .20$ , the difference between true and false posts was significant at  $p < .001$  for all three health contexts (see Table 3).

We also conducted two exploratory regression analyses in which we modeled random intercepts for subject and for article and random slopes for topic and truth. These models showed nearly identical results as the preregistered analyses and are available in the online supplemental materials.

### Research Question 1: Are Some People Generally More Susceptible to Online Health Misinformation Than Others, Regardless of the Particular Health Topic?

Results showed strong positive correlations among accuracy judgments for false posts about statins, cancer, and the HPV

vaccine ( $r_s = .70-.71, p_s < .001$ ). These results indicate, as predicted, that people who believe misinformation about vaccines are likely to also believe misinformation about statins and cancer treatment, and vice versa. There were also moderately strong correlations among judgments for true posts about statins, cancer, and the HPV vaccine ( $r_s = .55-.57, p_s < .001$ ). Also as predicted, correlations between accuracy judgments for true and false information within the same health topic (e.g., statin true correlated with statin false) were negligible or negative ( $r_s = -.10-.04$ ). A series of Fisher's  $r$ -to- $z$  comparisons indicated that these correlations were similar across all health contexts (all  $p_s > .652$ ; see online supplemental materials). This further indicates that a person who is susceptible to health misinformation in one of these health contexts is also more likely to fall for misinformation in the other health contexts.

### Research Question 2: What Are the Psychosocial Predictors of Misinformation Susceptibility?

Correlation analyses showed that across all three types of health information—statins, cancer, and the HPV vaccine—participants were more likely to perceive misinformation as accurate *and* influential if they spent more hours per day on social media ( $r_s = .12-.20$ , all  $p_s < .001$ ), whereas days per week on social media was not associated with any misinformation judgments, all  $p_s > .05$ . Older participants and those with higher household income perceived all three types of misinformation as less accurate and influential (age:  $r_s = -.11$  to  $-.22$ ; income:  $r_s = -.09$  to  $-.18$ , all  $p_s < .01$ ). None of the health-related measures (health status, insurance, high cholesterol, cancer diagnosis, HPV vaccine-aged child) were strongly or consistently associated with perceived accuracy and influence of any type of misinformation, except for statin use. Participants who were currently taking a statin perceived all three types of misinformation as less accurate and influential than participants not taking a statin ( $r_s = -.07$  to  $-.22, p_s < .05$ ).

Full correlation results are in the online supplemental materials, and simultaneous regression results are displayed in Table 4. These regressions estimate the unique variance contributed by each hypothesis-relevant measure, adjusting for health-related characteristics, social media use, and demographics. Table 4 shows that after adjusting for other measures, hours per day on social media and demographic measures were no longer strong or consistent predictors of the perceived accuracy or influence of misinformation. The measures that showed a high degree of predictive consistency across health contexts were related to the psychological hypotheses. In particular, individuals who were higher in literacy or education (i.e., the deficit hypothesis measures) were less likely to believe misinformation was true or would influence their decisions. Individuals with positive attitudes toward complementary and alternative medicine and individuals who distrusted the health care system were more likely to believe that all three types of misinformation were true and would influence their decisions. In an exploratory stepwise regression that combined accuracy judgments for all three health topics into one mean score, we entered education, health literacy, CAM attitudes, and health care system trust in Step 1 and all other predictors in Step 2. These analyses showed that those four measures together accounted for 19% of the variance in perceived accuracy of misinformation,

**Table 2**  
*Sample Characteristics*

Variable	<i>n (%)</i> or <i>M (SD)</i>	Scale
Health status	<i>M</i> = 2.59, <i>SD</i> = 0.99	1–5 Likert scale; 1 = <i>excellent</i> , 5 = <i>poor</i>
Health insurance status, <i>n (%)</i>		Yes/no
Yes	866 (93.8)	
No	50 (5.4)	
Missing	7 (0.8)	
High cholesterol, <i>n (%)</i>		Yes/no
Yes	462 (50.1)	
No	460 (49.8)	
Missing	1 (0.1)	
Take statin, <i>n (%)</i>		Yes/no/not sure
Yes	319 (34.6)	
No	585 (63.4)	
Not sure	19 (2.1)	
Cancer diagnosis, <i>n (%)</i>		Yes/no
Yes	131 (14.2)	
No	792 (85.8)	
Parent, <i>n (%)</i>		Yes/no
Yes	570 (61.8)	
No	352 (38.1)	
Missing	1 (0.1)	
Child 10–18, <i>n (%)</i>		Yes/no
Yes	100 (10.8)	
No	822 (89.1)	
Missing	1 (0.1)	
10–18-year-old child received HPV vaccine? <i>n (%)</i>		Categorical
Yes	206 (22.6)	
No, not yet	104 (11.2)	
No, I do not want my child to receive it	243 (26.3)	
Social media use: Days per week	<i>M</i> = 5.24, <i>SD</i> = 2.47	0–7 days per week
Social media use: Hours per day	<i>M</i> = 1.94, <i>SD</i> = 1.33	0–6 Likert; 0 = <i>none</i> , 1 = 30 min, 2 = 30–60 min, 6 = <i>more than 5 hr</i>
Social media type, <i>n (%)</i>		Select all that apply
Facebook	736 (79.7)	
YouTube	430 (46.6)	
Instagram	228 (24.7)	
Twitter	219 (23.7)	
Reddit	41 (4.4)	
Tumblr	18 (2.0)	
Myspace	12 (1.3)	
Other	42 (4.6)	
None	50 (5.4)	
Age	<i>M</i> = 60.79, <i>SD</i> = 9.75	Continuous
Gender		Categorical
Male	366 (39.7)	
Female	551 (59.7)	
Transgender	5 (0.5)	
Other	0 (0)	
Race/ethnicity		Categorical
White	698 (75.6)	
African American	146 (15.8)	
Asian/Asian American	40 (4.3)	
American Indian	6 (0.7)	
Native Hawaiian	2 (0.2)	
Other	31 (3.4)	
Hispanic	147 (15.9)	
Education		Categorical
Less than high school	24 (2.6)	
High school/GED	164 (17.8)	
Trade school	32 (3.5)	
Some college	164 (17.8)	
Associates/bachelor's degree	365 (39.6)	
Master's degree	137 (14.8)	

(table continues)

Table 2 (Continued)

Variable	<i>n</i> (%) or <i>M</i> ( <i>SD</i> )	Scale
Doctoral/professional degree	36 (3.9)	
Missing	1 (0.1%)	
Household income	<i>M</i> = 5.15, <i>SD</i> = 2.65	Ordinal 1–9 scale; 1 = less than \$20,000, 5 = \$50,000–59,000, 9 = \$150,000+
Work in medical field		Yes/no
Yes	55 (6.0)	
No	855 (92.6)	
Missing	13 (1.4)	

Note. HPV = Human Papilloma Virus.

whereas all other predictors combined (including health measures and demographics) explained just 8% of the variance.

The cognitive miserliness hypothesis was not as strongly supported. Although greater reflective reasoning (as measured by the CRT) was correlated with less perceived accuracy and influence of all three types of misinformation ( $r_s = -.16$  to  $-.26$ ,  $p_s < .001$ ), Table 4 shows that after adjusting for other variables, the CRT was predictive of judgments for cancer and vaccination but not statins, making the CRT a somewhat less consistent unique predictor of misinformation beliefs as compared to CAM attitudes, trust in health care, literacy, and education.

Our hypothesis that medical minimizers would be more susceptible to misinformation than maximizers was also not supported, and surprisingly, maximizers were significantly more susceptible to misinformation than minimizers (see Table 4). Notable measures that did not predict misinformation susceptibility consistently or at all were holistic health beliefs, belief in science, and health-related conditions that would have made the information more personally relevant, such as having high cholesterol or cancer.

## Discussion

Health misinformation is circulated widely on social media and can influence health decisions. The present research found that belief in misinformation about statins, cancer treatment, and the HPV vaccine were highly correlated, indicating that an individual who believes misinformation about one of these topics is also at risk of being influenced by misinformation about the other two topics. This study therefore provides evidence that certain individuals are generally more susceptible to health misinformation across at least three (and possibly more) health contexts.

Knowing who is susceptible to online misinformation is a key step toward intervention because effective health messaging depends on

being able to identify the appropriate target audience(s) and creating effective messages for those audiences (Witte et al., 2001). Individual characteristics that would make each health topic more personally relevant—for example, being diagnosed with high cholesterol, having cancer, having an HPV vaccine-aged child—were mostly unpredictable of misinformation susceptibility. The one exception was that individuals who were currently taking a statin were less susceptible to statin misinformation than individuals who were not. These individuals may have been protected from believing statin misinformation for a few reasons; for example, they may have received quality statin information from their doctor, they might have been motivated to disbelieve information that conflicted with their behavior, or they may be individuals who have already encountered these ideas and decided to reject them previously.

We considered four psychosocial hypotheses for why some people are more susceptible to misinformation than others: (a) the deficit hypothesis, (b) health related attitudes, (c) trust, and (d) cognitive miserliness. These were not mutually exclusive hypotheses, and we found that three were supported. In particular, less educational attainment and lower health literacy (the deficit hypothesis measures), greater positive attitudes toward alternative medicine, and lower health care system trust were each uniquely and consistently associated with greater misinformation susceptibility. Together, these variables explained more than twice as much variance in misinformation susceptibility than all other predictors combined. These results suggest that interventions might be targeted to reach these populations of people, rather than tailored for people with specific health problems.

These results also show substantial convergence with previously identified predictors of vaccine hesitancy. Prior research has similarly reported that individuals who express greater vaccine hesitancy tend to have less educational attainment (according to a 2019 nationally representative U.S. survey; Kempe et al., 2020), more positive attitudes toward alternative medicine, and less trust

Table 3

*M* (*SD*) Perceived Accuracy and Influence Ratings for All Six Types of Information and Difference Between Mean Ratings of True and False Posts

Judgment	Health context	True posts	False posts	Difference
Perceived accuracy	Statins	2.83 (0.51)	2.31 (0.61)	0.52***
	Cancer	3.04 (0.53)	2.07 (0.71)	0.97***
	HPV vaccine	2.84 (0.57)	2.27 (0.68)	0.57***
Perceived influence	Statins	2.66 (0.67)	2.30 (0.72)	0.36***
	Cancer	2.86 (0.67)	2.11 (0.80)	0.75***
	HPV vaccine	2.74 (0.74)	2.28 (0.79)	0.46***

Note. HPV = Human Papilloma Virus. Scales ranged from 1–4.

\*\*\* $p < .001$ .

**Table 4**

*Standardized  $\beta$  Coefficients From Simultaneous Linear Regressions Predicting Perceived Accuracy and Perceived Influence of Misinformation*

Hypothesis/control variables	Measure	Perceived accuracy			Perceived influence		
		Statins	Cancer	HPV vaccine	Statins	Cancer	HPV vaccine
Deficit hypothesis	Health literacy	-.14***	-.10**	-.15***	-.11***	-.09**	-.10**
	Education	-.14***	-.10**	-.10**	-.09**	-.11**	-.10**
Health-related attitudes	CAM	.25***	.27***	.24***	.22***	.22***	.19***
	HH	.08*	.00	.07*	.06*	-.01	.03
	MMS	.14***	.19***	.16***	.11**	.14***	.12**
Trust	Healthcare system trust	-.14***	-.17***	-.10**	-.13***	-.17***	-.13***
	Belief in science	-.07*	-.01	-.03	-.09**	-.02	-.08*
Cognitive miserliness	CRT	-.05	-.14***	-.10**	-.05	-.13**	-.08*
Control variables	Health status	-.04	-.02	-.05	-.02	-.05	-.06
	Insurance status	.03	.00	.00	.01	-.02	.00
	High cholesterol	.06	.03	.02	.05	.03	.08*
	Take statin	-.22***	-.05	-.04	-.19***	-.03	-.07*
	Cancer diagnosis	.03	-.03	-.02	.01	-.03	.01
	HPV vaccine aged child	.02	.02	-.01	.00	.00	-.01
	Social media: Days per week	.01	.00	-.05	.00	.00	-.05
	Social media: Hours per day	.01	.08**	.05	.05	.10**	.07*
	Age	-.06	-.11**	-.05	-.02	-.09**	-.03
	Gender	.02	.05	.01	-.02	.02	-.02
	Race	-.05	-.05	.01	-.03	-.07*	-.04
	Household income	.01	-.06	-.02	.02	-.02	-.01
	Work in medical field	.02	.00	-.05	.02	.02	-.04
	Perceived accuracy/influence of true posts	.14***	.10**	-.06	.43***	.33***	.26***

*Note.* Each column represents complete results from a single regression model. For all yes/no outcomes, 1 = yes, 0 = no. Race coded as White = 1, non-White = 0. Transgender participants coded as identified gender. Income and education are treated as continuous predictors for the sake of these analyses. CAM = complementary and alternative medicine; HPV = Human Papilloma Virus; HH = holistic health; MMS = Medical Maximizer-Minimizer Scale; CRT = Cognitive Reflection Test.

\*  $p < .05$ . \*\*  $p < .01$ . \*\*\*  $p < .001$ .

in health care (Benin et al., 2006; Browne et al., 2015). The present results also converge with findings from a recent study showing that people who are susceptible to COVID-19 misinformation tend to have lower science knowledge and are more likely to be medical maximizers (we did not predict this direction of effect for maximizers, but it appears to be replicable; Pennycook et al., 2020).

With regard to the cognitive miserliness hypothesis, our findings for the CRT were mixed: The CRT was correlated with all misinformation judgments, but associations with statin misinformation judgments were not significant after adjusting for covariates in regression, while associations for cancer and vaccination misinformation remained significant. Prior research has found that the CRT is not related to vaccine hesitancy but is related to susceptibility to both COVID-19 misinformation and political misinformation (Browne et al., 2015; Pennycook & Rand, 2020). Differences across studies with regard to the predictive power of the CRT may be due to the nature of the controlled-for variables, as well as the importance of the skills that are measured by the CRT for the judgment at hand.

### On Identifying and Addressing Health Misinformation

The social media posts included in this study were ones that our team unanimously agreed were either true/mostly true or false/mostly false on the basis of our collective expertise. In some cases, identifying false information was clear-cut. For example, there is no evidence that marijuana, ginger, or dandelion root are effective cures for cancer, counter to claims in cancer-related posts.

However, most misinformation has at least a kernel of truth to it, and we found that evaluating information often required thoughtfulness and expertise, particularly for statin information. The smaller mean difference between ratings of true and false posts for statins, relative to cancer posts, may have occurred because the cancer misinformation was more obviously false than the statin misinformation.

For example, one of the statin posts that we identified as mostly false claimed that statins cause a number of harmful side effects. While the evidence suggests that some of those side effects are indeed caused by statins, others are not supported by any evidence, and some appear to be “nocebo” effects (wherein negative expectations cause the experience of side effects even in patients receiving a placebo; Slomski, 2017). Another statin post claimed that “red yeast rice lowers cholesterol as well as a statin.” While red yeast rice does lower cholesterol, it is inferior to recommended moderate- and high-potency statins at reducing cholesterol and preventing heart attacks and death (Cannon et al., 2004; Li et al., 2014). Hence, a person reading that post without the requisite knowledge of the medical literature would be misinformed about the effectiveness of red yeast rice compared to statins.

Given the observed strong correlations between participants’ judgments of misinformation about cancer, statins, and the HPV vaccine, the present findings appear to be robust to the level of nuance or expertise needed to evaluate the truth value of this information. One potential implication is that people who are susceptible to health misinformation may be individuals who, perhaps because of lower health literacy, beliefs about alternative medicine



and distrust of the healthcare system, are attracted to strong claims that appear to go against the medical status quo. Overall, this points to the need for trusted medical experts to clarify and counteract misleading claims on social media, using evidence-based communication methods such as those described by Lewandowsky et al. (2012). At the same time, sometimes medical experts disagree on the quality of evidence that exists, and sometimes widely accepted recommendations are reversed as a result of being based on flawed or inadequate evidence (for numerous examples, see Prasad & Cifu, 2015). Hence, when identifying and correcting health misinformation, it is important for experts to offer a balanced perspective on the evidence that does exist and acknowledge the truth that may be embedded within misleading claims.

### Limitations and Future Directions

Although this work provides several novel insights, it is important to acknowledge limitations that could guide future research. We believe that our process for selecting true and false social media posts allowed us to obtain a fair representation of the kinds of content that had been shared on social media at the time of this study, but without random selection among all social media content (which would have been infeasible), it is possible that these results were biased by the specific posts that were selected. These results should therefore be replicated and extended using new social media posts selected using the same and alternative search methods. Relatedly, the posts that we selected were dependent on the landscape of health misinformation that currently exists on social media, which may change in the future. For example, the observed association between complementary and alternative medicine attitudes and misinformation susceptibility was likely due to the fact that much of the health misinformation that we found touted unproven alternative medical therapies or inaccurately critiqued evidence-supported medicine. Moreover, the present results might be limited to the three health topics examined (statins, cancer treatment, and the HPV vaccine). Future research should replicate and extend these findings in additional health contexts (e.g., misinformation about COVID-19) and examine the influence of additional factors such as the number of likes and shares that a post receives.

Another limitation is that we did not assess whether the claims in these posts were familiar or novel to participants. Certain misinformation correction techniques, such as inoculation (van der Linden et al., 2017), may be less effective when misinformation is familiar and has already been accepted as true. The fact that we observed strong correlations between belief in misinformation across topics is perhaps more surprising given that some participants might have been familiar with claims in one health context but not others. The predictive strength of CAM attitudes suggests that these posts may have been accepted by some participants because they were recognizably consistent with those attitudes, regardless of whether the specific ideas were familiar or new. Indeed, it may be just as difficult to dislodge a new idea that is consistent with one's attitudes as an old idea that has been previously accepted.

Finally, typical concerns about online samples—such as participants being more familiar with and likely to use technology to access health-related information—could be viewed as an advantage for this research. This survey was not nationally representative, which is why

we did not focus on the overall rates of belief in misinformation and instead focused on differences across health contexts and predictors of susceptibility. However, these types of online samples have been shown to replicate results of probability sample results (Mullinix et al., 2015), and this sample had race and education distributions that closely matched the U.S. population proportions. Even with all of the measures included to predict misinformation susceptibility, there was still substantial variance that remained unexplained, leaving considerable room for identification of other explanatory predictors. Future research should replicate these findings, exploring predictors of belief in misinformation in different U.S. samples as well as outside of the United States. It is also possible that there are interactions between predictors of misinformation, a possibility that should be explored. We hope that future research can use these findings to develop novel interventions and efficient dissemination of those interventions to reduce the influence and spread of health misinformation online.

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