Online Health Misinformation Susceptibility Increases Health Risk Behaviors and Vaccine Hesitancy: Evidence from Greece

Ioannis Moisoglou , Aglaia Katsiroumpa , Olympia Konstantakopoulou * , Aris Yfantis , Olga Galani , Maria Tsiachri , Panagiota Peleka , Zoe Katsiroumpa , Petros Galanis

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Article

Online Health Misinformation Susceptibility Increases Health Risk Behaviors and Vaccine Hesitancy: Evidence from Greece

Ioannis Moisoglou [1], Aglaia Katsiroumpa [2], Olympia Konstantakopoulou [3,*], Aris Yfantis [4], Olga Galani [5], Maria Tsiachri [2], Panagiota Peleka [2], Zoe Katsiroumpa [2] and Petros Galanis [2]

[1] Department of Nursing, University of Thessaly, 41500 Larissa, Greece
[2] Clinical Epidemiology Laboratory, Faculty of Nursing, National and Kapodistrian University of Athens, 11527, Athens, Greece
[3] Center for Health Services Management and Evaluation, Faculty of Nursing, National and Kapodistrian University of Athens, 11527, Athens, Greece
[4] Directorate of Secondary Education of Fthiotis, Special Vocational Education Laboratory of Fthiotis, 35100, Lamia, Greece
[5] Faculty of Nursing, University of West Attica, 12243 Athens, Greece
* Correspondence: olympiak1982@hotmail.com

Abstract

Background: Health-related misinformation is a pervasive phenomenon that expanded substantially during the COVID-19 pandemic, particularly regarding concerns about vaccine safety and effectiveness. **Objective:** To investigate the impact of online health misinformation susceptibility on health behaviors and vaccine hesitancy. **Methods:** A cross-sectional study was conducted in Greece, with data collected via an online survey during September 2025. We used the Health-Related Online Misinformation Susceptibility Scale to measure online health misinformation susceptibility. Health Behavior Inventory – Short Form was used to measure health behaviors, while Vaccine Hesitancy Scale (VHS) was used to measure participants' hesitancy towards vaccination. We performed multivariable analysis to identify the independent effect of health misinformation after adjustment for several confounders. **Results:** Multivariable linear regression analysis showed a positive association between online health misinformation susceptibility and diet score (adjusted coefficient beta = 0.026, 95% confidence interval [CI] = 0.006 to 0.046, p = 0.010) and anger and stress score (adjusted coefficient beta = 0.033, 95% CI = 0.013 to 0.052, p = 0.001). After adjustment for confounders, we found a positive association between online health misinformation susceptibility and score on the factors "lack of confidence" (adjusted coefficient beta = 0.016, 95% CI = 0.005 to 0.028, p = 0.006) and "risk perception" (adjusted coefficient beta = 0.023, 95% CI = 0.010 to 0.036, p = 0.001). **Conclusion:** Our findings suggest that higher susceptibility to online health misinformation is linked to poorer health behaviors and greater vaccine hesitancy.

Keywords: health misinformation; susceptibility; health behaviors; vaccine hesitancy; risk; fake news

1. Introduction

Citizens increasingly seek online information on a wide range of topics, among which health-related information constitutes a prominent area of interest. Such information-seeking behavior is not confined to the websites of healthcare or health-related organizations (e.g., hospitals or healthcare professionals) but also extends to social networking platforms. The scope of online health information is broad and encompasses general health information, specific diseases, medications and treatments, nutrition and physical activity, medical resources, disease-related symptoms, health promotion, as well as health-related news and policies [1,2]. Nevertheless, in many instances, the information

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received by users is not scientifically substantiated in accordance with current scientific evidence; however, it is often perceived as scientifically valid and useful, and is frequently reproduced and disseminated further through social media platforms [3,4]. False information that is shared without the intention to mislead or to cause harm is defined as misinformation [5]. Access to the internet, combined with the ease of information sharing through social media platforms, facilitates the rapid dissemination of misinformation.

Vaccines have historically been the target of opposition primarily from the anti-vaccination movement, which has raised concerns regarding their safety and effectiveness. These concerns have included allegations that vaccines may cause brain damage, seizures, intellectual disability, and autism. As a consequence, childhood vaccination coverage declined, leading to the resurgence of infectious diseases [6]. This phenomenon of vaccine skepticism was particularly pronounced during the COVID-19 pandemic, during which widespread misinformation circulated regarding medical issues, vaccine development processes, and conspiracy theories, ultimately exerting a negative influence on vaccination intention [7–9].

Misinformation also affects other domains of health-related behaviors, including substance use and smoking, as well as dietary habits. Specifically, with regard to smoking and illicit drug use, misinformation primarily concerns the purported safety of e-cigarettes and their alleged positive role in smoking cessation, as well as claims regarding the safe and effective use of drugs in the absence of scientific evidence [10,11]. Also, online nutrition-related information is often inaccurate and of low quality [12]. Misinformation related to nutrition may pertain to claims concerning weight loss, as well as to purported beneficial effects of specific foods on the prevention and treatment of chronic diseases [13–15]. Fake news and misinformation can also exert a significant impact on mental health, affecting both individuals who disseminate such content and those who are exposed to it [16,17].

The characteristics of individuals who are vulnerable to the consumption of misinformation include higher levels of perceptual bias, increased depressive symptoms, and lower educational attainment [18]. Furthermore, individuals who report high levels of distrust, particularly toward governmental institutions, are more likely to be misinformed [19]. Also, people with lower trust in scientists and those who believe in conspiracy behaviors, show higher levels of misinformation susceptibility [20]. Especially with regard to vulnerability to health-related misinformation, identified predictive factors include health-related anxiety, pre-existing misinformation beliefs, and repeated exposure to health misinformation, as well as female gender and lower socioeconomic status [21]. Among nurses, higher levels of trust in scientists, possession of an MSc or PhD degree, and expressed interest in politics were associated with reduced susceptibility to online health misinformation [22].

Building upon the aforementioned framework, this study sought to investigate the impact of online health misinformation susceptibility on health behaviors and vaccine hesitancy.

2. Materials and Methods

2.1. Study Design

A cross-sectional study was conducted in Greece, with data collected via an online survey during September 2025. The questionnaire was developed using Google Forms and disseminated through social media platforms, including Facebook, Instagram, and LinkedIn, yielding a convenience sample. Eligibility criteria required participants to (1) be adults, (2) spend at least 30 minutes daily on the internet or social media to ensure a minimum exposure to online information, and (3) provide informed consent. The study adhered to the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines [23]. Sample size was calculated using G*Power v.3.1.9.2. With one predictor and six confounders included in the multivariable models, an anticipated effect size of 0.04 for predictor-outcome association, a statistical power of 95%, and a 5% type I error, the required sample size was estimated at 327 participants.

2.2. Measurements

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We collected data on various demographic characteristics of the participants, including gender (male or female), age (treated as a continuous variable), and educational attainment (elementary school, middle school, high school, or university degree). Financial status was assessed using a self-rated scale ranging from 0 (very poor) to 10 (excellent). Participants also rated their digital literacy on a scale from 0 (very poor) to 10 (very good) and reported the number of hours spent daily on the internet or/and social media (continuous variable).

We used the Health-Related Online Misinformation Susceptibility Scale (HR-OMISS) [24] to measure online health misinformation susceptibility in our sample. The HR-OMISS is an adapted version of the Online Misinformation Susceptibility Scale (OMISS) [25] that measures online misinformation susceptibility in general, while the HR-OMISS measures specifically online health misinformation susceptibility. The HR-OMISS includes nine items and answers are on a five-point Likert scale; never (5), rarely (4), sometimes (3), very often (2), always (1). Total score ranges from 9 to 45. Higher scores indicate higher misinformation susceptibility. We used the valid Greek version of the HR-OMISS [24]. In our study, the Cronbach's alpha for the HR-OMISS was 0.883.

Health Behavior Inventory – Short Form (HBI-SF) [26]was used to measure health behaviors among our participants. The HBI-SF includes 12 items and answers are on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). Six items are reverse scored so that higher scores on all items indicate a greater degree of health risk. The HBI-SF includes four factors; diet (three items); proper use of health care resources (three items); anger and stress (three items); and substance use (three items). Score on each factor is obtained by summing answers and dividing by the number of items. After all, score on each factor ranges from 1 to 7 with higher values indicate higher level of health risk behaviors. We used the valid Greek version of the HBI-SF [27]. In our study, the Cronbach's alpha for the four factors of the HBI-SF ranged from 0.713 to 0.824.

Vaccine Hesitancy Scale (VHS) [28] was used to measure participants' hesitancy towards vaccination. The VHS includes 10 items and answers are on a 5-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). Seven items are reverse scored so that higher scores on all items indicate higher levels of vaccine hesitancy. The VHS includes two factors; lack of confidence (seven items), and risk perception (three items). Score on each factor is obtained by summing answers and dividing by the number of items. After all, score on each factor ranges from 1 to 5. We used the valid Greek version of the VHS [29]. In our study, the Cronbach's alpha for the factors "lack of confidence" and "risk perception" was 0.917 and 0.704, respectively.

2.3. Ethical Issues

The study protocol received formal approval from the Ethics Committee of the Faculty of Nursing at the National and Kapodistrian University of Athens (approval No. 75, July 13, 2025). The research complied with the ethical principles outlined in the Declaration of Helsinki [30]. Data collection was conducted anonymously and on a voluntary basis, following a comprehensive briefing on the study's objectives and procedures, after which participants provided informed consent.

2.4. Statistical Analysis

Categorical variables were summarized as frequencies and percentages, whereas continuous variables were expressed as means with standard deviations (SD) and medians with interquartile ranges. Assessment of normality was performed using the Kolmogorov-Smirnov test and Q-Q plots, confirming that continuous variables exhibited a normal distribution. Our independent variable was online health misinformation susceptibility, while the dependent variables included health behaviors and vaccine hesitancy. Given the normal distribution of the dependent variables, linear regression analysis was applied. Initially, simple linear regression analysis was conducted to examine univariate associations, followed by a multivariable regression analysis to estimate the independent effect of online health misinformation susceptibility. Results are presented as unadjusted and adjusted beta coefficients, along with 95% confidence intervals (CI) and p-values. We calculated the Durbin-Watson statistic to examine if the residuals in the multivariable linear regression models are autocorrelated.

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The Durbin-Watson statistic takes values from 0 to 4; values near 2 are acceptable since indicate non-autocorrelation, while values toward 0 indicate positive autocorrelation, and values toward 4 indicate negative autocorrelation, and, thus, are unacceptable. Also, we calculated Variance Inflation Factor for the independent factors to examine collinearity in the multivariable linear regression models. Variance Inflation Factors greater than 5 suggest serious collinearity. The Durbin-Watson statistic and Variance Inflation Factors in our multivariable models were acceptable (see Tables 4 and 5). Additionally, Pearson's correlation coefficients were calculated to assess correlations between normally distributed scale scores. A p-value < 0.05 was considered statistically significant. We used the IBM SPSS 28.0 (IBM Corp. Released 2021. IBM SPSS Statistics for Windows, Version 28.0. Armonk, NY: IBM Corp) for the analysis.

3. Results

3.1. Demographic Characteristics

The study sample consisted of 402 participants, of whom 76.6% were female. The mean age was 48.74 years (SD = 9.52), with a median age of 50 years and an interquartile range of 10 years. The average financial status score was 5.60 (SD = 1.45), while the median score was 6 (interquartile range = 2). Digital literacy exhibited a mean score of 7.49 (SD = 1.90) and a median of 8 (interquartile range = 3). On average, participants reported spending 3 hours per day on web/social media platforms (SD = 2.36), with a median of 2 hours and an interquartile range of 2.5 hours. Table 1 shows the demographic details of our participants.

Table 1. Demographic characteristics of the study sample (n=402).

Characteristics	N	%
Gender		
Males	94	23.4
Females	308	76.6
Age[a]	48.74	9.52
Educational level		
High school	40	10.0
University	382	90.0
Financial status[a]	5.60	1.45
Digital literacy[a]	7.49	1.90
Daily time in web/social media (hours)[a]	3.00	2.36

[a] mean, standard deviation.

3.2. Study Scales

The mean score on the HR-OMISS scale was 22.28. In relation to health-related behaviors, the average scores for the dimensions "diet", "appropriate utilization of health care resources", "anger and stress management", and "substance use" were 2.94, 2.64, 4.10, and 1.58, respectively. Regarding vaccine hesitancy, the mean score for lack of confidence was 3.92, whereas the mean score for risk perception was 3.06. A detailed summary of descriptive statistics for all study measures is presented in Table 2.

Table 2. Descriptive statistics for the study scales (n=402).

Scale	Mean	Standard deviation	Median	Interquartile range
Health-Related Online Misinformation Susceptibility Scale	22.28	6.82	21	8
Health Behavior Inventory – Short Form				
Diet	2.94	1.37	2.67	2

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Proper use of health care resources	2.64	1.49	2.33	2.33
Anger and stress	4.10	1.33	4.33	1.67
Substance use	1.58	0.89	1	1
Vaccine Hesitancy Scale				
Lack of confidence	3.92	0.78	4	1.29
Risk perception	3.06	0.90	3	1.33

Table 3 summarizes the correlations among the study variables. Online health misinformation susceptibility demonstrated positive correlations with diet score (r = 0.144, p = 0.004), anger and stress score (r = 0.147, p = 0.003), lack of confidence score (r = 0.119, p = 0.017), and risk perception score (r = 0.199, p < 0.001). These findings indicate that higher susceptibility to online health misinformation was linked to poorer health behaviors and greater vaccine hesitancy.

Table 3. Pearson's correlation coefficients for the study scales (n=402).

Scale	2	3	4	5	6	7
1. Health-Related Online Misinformation Susceptibility Scale	0.144**	0.012	0.147**	0.084	0.119*	0.199**
Health Behavior Inventory – Short Form						
2. Diet		0.457**	0.041	0.085	0.084	0.098*
3. Proper use of health care resources			0.082	0.100*	0.188**	0.096
4. Anger and stress				0.131**	0.023	0.093
5. Substance use					0.019	0.048
Vaccine Hesitancy Scale						
6. Lack of confidence						0.288**
7. Risk perception						

* p-value < 0.05 ** p-value < 0.01.

3.3. Dependent Variable: Health Behaviors

Table 4 shows the results from the linear regression analysis with score on the Health Behavior Inventory – Short Form as the dependent variable. Multivariable linear regression analysis showed a positive association between online health misinformation susceptibility and diet score (adjusted coefficient beta = 0.026, 95% CI = 0.006 to 0.046, p = 0.010) and anger and stress score (adjusted coefficient beta = 0.033, 95% CI = 0.013 to 0.052, p = 0.001). We did not find statistically significant associations between online health misinformation susceptibility and scores on the factors "proper use of health care resources" and "substance use".

Table 4. Linear regression models with score on the Health-Related Online Misinformation Susceptibility Scale as the independent variable and scores on the four factors of the Health Behavior Inventory – Short Form as the dependent variables (n=402).

Dependent variables	Univariate models			Multivariable model[a]		
	Unadjusted coefficient beta	95% CI for beta	P-value	Adjusted coefficient beta	95% CI for beta	P-value
Diet[b]	0.029	0.009 to 0.049	0.004	0.026	0.006 to 0.046	0.010
Proper use of health care resources[c]	0.003	-0.019 to 0.024	0.803	0.000	-0.022 to 0.021	0.984
Anger and stress[d]	0.029	0.010 to 0.048	0.003	0.033	0.013 to 0.052	0.001
Substance use[e]	0.011	-0.002 to 0.024	0.092	0.007	-0.006 to 0.020	0.264

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[a] Models are adjusted for gender, age, educational level, financial status, digital literacy, and daily time in web/social media [b] R^2 for the final multivariable model = 4.0%; p-value for ANOVA = 0.002; Durbin-Watson statistic = 1.921; Variance Inflation Factor = 1.068 [c] R^2 for the final multivariable model = 4.1%; p-value for ANOVA < 0.001; Durbin-Watson statistic = 1.863; Variance Inflation Factor = 1.068 [d] R^2 for the final multivariable model = 5.2%; p-value for ANOVA < 0.001; Durbin-Watson statistic = 2.047; Variance Inflation Factor = 1.068 [e] R^2 for the final multivariable model = 4.5%; p-value for ANOVA = 0.001; Durbin-Watson statistic = 1.880; Variance Inflation Factor = 1.068 CI: confidence interval.

3.4. Dependent Variable: Vaccine Hesitancy

Table 5 shows the results from the linear regression analysis with score on the Vaccine Hesitancy Scale as the dependent variable. After adjustment for confounders we found a positive association between online health misinformation susceptibility and score on the factors "lack of confidence" (adjusted coefficient beta = 0.016, 95% CI = 0.005 to 0.028, p = 0.006) and "risk perception" (adjusted coefficient beta = 0.023, 95% CI = 0.010 to 0.036, p = 0.001).

Table 5. Linear regression models with score on the Health-Related Online Misinformation Susceptibility Scale as the independent variable and scores on the two factors of the Vaccine Hesitancy Scale as the dependent variables (n=402).

Dependent variables	Univariate models			Multivariable model[a]		
	Unadjusted coefficient beta	95% CI for beta	P-value	Adjusted coefficient beta	95% CI for beta	P-value
Lack of confidence[b]	0.014	0.003 to 0.025	0.017	0.016	0.005 to 0.028	0.006
Risk perception[c]	0.026	0.013 to 0.039	<0.001	0.023	0.010 to 0.036	0.001

[a] Models are adjusted for gender, age, educational level, financial status, digital literacy, and daily time in web/social media [b] R^2 for the final multivariable model = 3.5%; p-value for ANOVA = 0.004; Durbin-Watson statistic = 1.656; Variance Inflation Factor = 1.068 [c] R^2 for the final multivariable model = 6.1%; p-value for ANOVA < 0.001; Durbin-Watson statistic = 1.829; Variance Inflation Factor = 1.068 CI: confidence interval.

4. Discussion

The present study demonstrated a significant association between susceptibility to online health misinformation and poorer health behaviors, as well as increased vaccine hesitancy. Regarding vaccine hesitancy, our findings are consistent with those reported in the existing literature [7]. Vaccination has historically been accompanied by a degree of skepticism, particularly concerning vaccine safety, a phenomenon that is further amplified when a novel vaccine is introduced, as was the case with the COVID-19 vaccines [31]. Unsubstantiated concerns about vaccine safety, lacking scientific evidence, are frequently propagated by the anti-vaccination movement. By exploiting social media platforms, this movement disseminates misinformation and fake news, which are easily and rapidly amplified and reproduced [32]. The more frequently a false claim is repeated and disseminated, the greater the likelihood that individuals will come to accept it as true [33]. In the domain of health-related information, repeated exposure to health misinformation actively fosters its acceptance [21] and can directly contribute to the development of vaccine hesitancy [34]. Since vaccine hesitancy has not only individual-level consequences but also significant implications for public health, it is essential to first investigate the factors that contribute to health misinformation hesitancy, as well as to identify the population groups that are more susceptible to accepting health-related misinformation. Individuals with lower educational attainment, members of minority populations, those with limited health literacy, people who exhibit distrust toward the healthcare system, individuals holding positive attitudes toward alternative medicine, persons with specific political orientations, and those with limited analytical thinking skills are more susceptible to health

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misinformation [35–37]. Healthcare professionals constitute a key determinant in mitigating susceptibility to health misinformation, particularly regarding vaccine acceptance. Empirical evidence indicates that individuals who place greater trust in scientists and healthcare professionals demonstrate lower susceptibility to health-related misinformation and exhibit a higher likelihood of accepting vaccination [35,38]. Consequently, healthcare professionals should possess the requisite knowledge and skills to respond effectively to the questions and concerns of citizens and patients, and to be able to critically challenge and counteract misinformation that may have been erroneously adopted as scientifically substantiated.

Regarding health-related behaviors, the present study demonstrated a significant association between exposure to misinformation and dietary practices, as well as elevated levels of anger and stress. Misinformation regarding food and nutrition is particularly prevalent on social media platforms. Such content frequently includes claims about “miracle diets” and broader forms of dietary misinformation related to specific pathologies, including unfounded assertions concerning disease prevention or treatment, as well as the enhancement of immune system function [39]. Individuals with higher levels of misinformation are more likely to disseminate inaccurate food safety information online [40]. The source of nutrition-related information plays a crucial role, with individuals who place trust in nutrition professionals being more likely to adopt higher-quality dietary patterns [41].

Misinformation can adversely affect the mental health and emotional well-being of individuals who consume and disseminate it, who may exhibit symptoms of anxiety, depression, posttraumatic stress disorder and psychological distress, such as confusion, fear, uncertainty, panic, agoraphobia, obsessive–compulsive manifestations, and somatization [16,42,43]. The way misinformation affects mental health may be interpreted in multiple ways. Misinformation related to highly adverse outcomes (e.g., death or severe disability) can elicit anxiety, fear, or even panic, as individuals may perceive these outcomes as posing a personal threat. A characteristic example is the alleged association between vaccination and autism, whereby parents may be negatively influenced by this false claim. Furthermore, misinformation suggesting that COVID-19 vaccines contain toxic substances may provoke feelings of anger, stemming from the assumption that people’s lives are being endangered without their knowledge or consent.

The multifaceted impacts of misinformation render it imperative that citizens possess the appropriate skills to critically appraise both the credibility of online sources from which they seek health-related information and the validity of content disseminated through social media platforms. Experimental studies have demonstrated that the acquisition of skills related to literacy concepts, including information, news, media, and digital literacies, significantly enhances participants’ ability to identify fake news and misinformation [44–47]. These programs should be designed to be applicable to both school pupils and university students, as they are not only direct consumers of misinformation, but also citizens who, throughout their lives, will frequently seek health-related information through online sources [48,49]. Recently in Greece, the Minister of Education announced the pilot implementation of educational programs for lower and upper secondary school students aimed at strengthening their skills in identifying fake news.

The present study has several limitations. First, its cross-sectional design precludes the establishment of causal relationships among the examined variables. In addition, the demographic characteristics of the participants could have included further variables, such as occupation, prior exposure to misinformation, and training in misinformation recognition. Consequently, future studies could explore the potential confounding role of these variables to establish a more valid association between online health misinformation susceptibility and health behaviors and vaccine hesitancy. Moreover, we used self-reported instruments to measure online health misinformation susceptibility, health behaviors and vaccine hesitancy and therefore information bias is probable in our study. Although valid instruments were employed to assess the study variables, participants may have responded in a socially desirable manner, potentially leading to an underestimation of misinformation susceptibility, an overreporting of favorable health behaviors, and a reduced

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indication of vaccine hesitancy. Additionally, our convenience sample through an online survey does not allow us to generalize our findings in the general population of Greece. Thus, further studies with random, stratified and representative samples are essential to improve our findings regarding the association between online health misinformation susceptibility, health behaviors and vaccine hesitancy. In this context, further studies in other countries with different cultural settings will add significant evidence in this research topic.

5. Conclusions

The present study demonstrates that susceptibility to online health-related misinformation is not merely an individual-level cognitive vulnerability but a broader public health and policy challenge with measurable consequences for health behaviors and vaccine confidence. The independent associations identified between misinformation susceptibility, maladaptive health behaviors, and vaccine hesitancy underscore the need to conceptualize health misinformation as a systemic risk factor that undermines population health outcomes and the effectiveness of public health interventions.

From a policy standpoint, these findings call for the formal integration of misinformation mitigation into national public health strategies, vaccination policies, and pandemic preparedness frameworks. Governments and public health authorities should establish regulatory and governance mechanisms that promote accountability and transparency in digital health information ecosystems, including structured collaboration with social media platforms to curb the spread of demonstrably false or misleading health content. Moreover, investment in population-wide digital health literacy should be treated as a core public health priority, with standardized curricula embedded across educational systems and continuing professional development programs for healthcare workers.

At the healthcare system level, policies should support the institutionalization of misinformation sensitive communication practices, enabling healthcare professionals to systematically assess misinformation exposure and address vaccine-related concerns through evidence-based, trust-building dialogue. In addition, surveillance systems capable of monitoring misinformation trends and their behavioral impacts should be developed to inform real-time policy responses. Collectively, these policy actions are essential to safeguard evidence-based health decision-making, strengthen vaccine confidence, and enhance societal resilience against future public health threats driven by the rapid dissemination of online health misinformation.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Ethics Committee of the Faculty of Nursing, National and Kapodistrian University of Athens approved our study protocol (approval No. 75, July 13, 2025).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data used in this study are openly available in Figshare at: https://doi.org/10.6084/m9.figshare.30675122

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References

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1. Zhao, Y.; Zhang, J. Consumer Health Information Seeking in Social Media: A Literature Review. *Health Information & Libraries Journal* **2017**, *34*, 268–283, doi:10.1111/hir.12192.
2. Zhao, Y.C.; Zhao, M.; Song, S. Online Health Information Seeking Behaviors Among Older Adults: Systematic Scoping Review. *Journal of Medical Internet Research* **2022**, *24*, e34790, doi:10.2196/34790.
3. Krishna, A.; Thompson, T.L. Misinformation About Health: A Review of Health Communication and Misinformation Scholarship. *American Behavioral Scientist* **2021**, *65*, 316–332, doi:10.1177/0002764219878223.
4. Sylvia Chou, W.-Y.; Gaysynsky, A.; Cappella, J.N. Where We Go From Here: Health Misinformation on Social Media. *Am J Public Health* **2020**, *110*, S273–S275, doi:10.2105/AJPH.2020.305905.
5. Aïmeur, E.; Amri, S.; Brassard, G. Fake News, Disinformation and Misinformation in Social Media: A Review. *Soc. Netw. Anal. Min.* **2023**, *13*, 30, doi:10.1007/s13278-023-01028-5.
6. Dubé, E.; Vivion, M.; MacDonald, N.E. Vaccine Hesitancy, Vaccine Refusal and the Anti-Vaccine Movement: Influence, Impact and Implications. *Expert Review of Vaccines* **2015**, *14*, 99–117, doi:10.1586/14760584.2015.964212.
7. Neely, S.R.; Eldredge, C.; Ersing, R.; Remington, C. Vaccine Hesitancy and Exposure to Misinformation: A Survey Analysis. *J GEN INTERN MED* **2022**, *37*, 179–187, doi:10.1007/s11606-021-07171-z.
8. Zimmerman, T.; Shiroma, K.; Fleischmann, K.R.; Xie, B.; Jia, C.; Verma, N.; Lee, M.K. Misinformation and COVID-19 Vaccine Hesitancy. *Vaccine* **2023**, *41*, 136–144, doi:10.1016/j.vaccine.2022.11.014.
9. Skafle, I.; Nordahl-Hansen, A.; Quintana, D.S.; Wynn, R.; Gabarron, E. Misinformation About COVID-19 Vaccines on Social Media: Rapid Review. *Journal of Medical Internet Research* **2022**, *24*, e37367, doi:10.2196/37367.
10. Suarez-Lledo, V.; Alvarez-Galvez, J. Prevalence of Health Misinformation on Social Media: Systematic Review. *Journal of Medical Internet Research* **2021**, *23*, e17187, doi:10.2196/17187.
11. Al Khaja, K.A.J.; AlKhaja, A.K.; Sequeira, R.P. Drug Information, Misinformation, and Disinformation on Social Media: A Content Analysis Study. *J Public Health Pol* **2018**, *39*, 343–357, doi:10.1057/s41271-018-0131-2.
12. Denniss, E.; Lindberg, R.; McNaughton, S.A. Quality and Accuracy of Online Nutrition-Related Information: A Systematic Review of Content Analysis Studies. *Public Health Nutrition* **2023**, *26*, 1345–1357, doi:10.1017/S1368980023000873.
13. Yussof, I.; Ab Muin, N.F.; Mohd, M.; Hatah, E.; Mohd Tahir, N.A.; Mohamed Shah, N. Breast Cancer Prevention and Treatment Misinformation on Twitter: An Analysis of Two Languages. *DIGITAL HEALTH* **2023**, *9*, 20552076231205742, doi:10.1177/20552076231205742.
14. Duarte, A.C.; Spiazzi, B.F.; Merello, E.N.; Amazarray, C.R.; Sulzbach de Andrade, L.; Socal, M.P.; Trujillo, A.J.; Brietzke, E.; Colpani, V.; Gerchman, F. Misinformation in Nutrition through the Case of Coconut Oil: An Online before-and-after Study. *Nutrition, Metabolism and Cardiovascular Diseases* **2022**, *32*, 1375–1384, doi:10.1016/j.numecd.2022.02.002.
15. Diyab, R.; Grgurevic, J.; Roy, R. Exploring Nutrition Misinformation on Social Media Platforms. *Proceedings of the Nutrition Society* **2025**, *84*, E8, doi:10.1017/S0029665125000187.
16. Verma, G.; Bhardwaj, A.; Aledavood, T.; De Choudhury, M.; Kumar, S. Examining the Impact of Sharing COVID-19 Misinformation Online on Mental Health. *Sci Rep* **2022**, *12*, 8045, doi:10.1038/s41598-022-11488-y.
17. Nguyen, T.T.; Nguyen, D.C.; Nguyen, H.T.; Do, H.T.; Ngo, T.; Pham, A.B.G.; Tran, T.Q.; Hoang, L.P.; Dang, H.; Boyer, L.; et al. Exposure to Fake News on Social Media, Coping Mechanisms, and Mental Health Impact among Vietnamese Adolescents and Young Adults. *Sci Rep* **2025**, *15*, 35117, doi:10.1038/s41598-025-19175-4.
18. Delmastro, M.; Paciello, M. Depression, Reduced Education, and Bias Perceptions as Risk Factors of Beliefs in Misinformation. *Sci Rep* **2022**, *12*, 16408, doi:10.1038/s41598-022-20640-7.
19. Maffioli, E.M.; Gonzalez, R. Are Socio-Demographic and Economic Characteristics Good Predictors of Misinformation during an Epidemic? *PLOS Global Public Health* **2022**, *2*, e0000279, doi:10.1371/journal.pgph.0000279.

 doi:10.20944/preprints202601.0698.v1

20. Katsiroumpa, A.; Moisoglou, I.; Konstantakopoulou, O.; Galani, O.; Tsiachri, M.; Galanis, P. Trust in Scientists and Conspiracy Beliefs Predict Online Misinformation Susceptibility and Fake News Detection: A Cross-Sectional Study in Greece, *medRxiv* **2025**, preprint, doi: 10.1101/2025.11.18.25340464
21. Pan, W.; Liu, D.; Fang, J. An Examination of Factors Contributing to the Acceptance of Online Health Misinformation. *Front. Psychol.* **2021**, *12*, doi:10.3389/fpsyg.2021.630268.
22. Katsiroumpa, A.; Moisoglou, I.; Konstantakopoulou, O.; Galanis, P. Factors Influencing Nurses' Susceptibility to Online Health Misinformation: Evidence from Greece, *medRxiv* **2025**, doi: 10.1101/2025.11.19.25340604
23. Von Elm, E.; Altman, D.G.; Egger, M.; Pocock, S.J.; Gøtzsche, P.C.; Vandenbroucke, J.P. The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) Statement: Guidelines for Reporting Observational Studies. *Journal of Clinical Epidemiology* **2008**, *61*, 344–349, doi:10.1016/j.jclinepi.2007.11.008.
24. Katsiroumpa, A.; Konstantakopoulou, O.; Gallos, P.; Moisoglou, I.; Mangoulia, P.; Galani, O.; Tsiachri, M.; Galanis, P. Online Misinformation Susceptibility Scale: An Adapted Version for Health-Related Misinformation. *Arch Hell Med* **2026**, under press.
25. Katsiroumpa, A.; Moisoglou, I.; Mangoulia, P.; Konstantakopoulou, O.; Gallos, P.; Tsiachri, M.; Galanis, P. The Online Misinformation Susceptibility Scale: Development and Initial Validation. *Healthcare* **2025**, *13*, 2252, doi:10.3390/healthcare13172252.
26. Levant, R.F.; Alto, K.M.; McKelvey, D.; Pardo, S.; Jadaszewski, S.; Richmond, K.; Keo-Meier, C.; Gerdes, Z. Development, Variance Composition, Measurement Invariance across Five Gender Identity Groups, and Validity of the Health Behavior Inventory–Short Form. *Psychology of Men & Masculinities* **2020**, *21*, 177–189, doi:10.1037/men0000215.
27. Katsiroumpa, A.; Moisoglou, I.; Galani, O.; Tsiachri, M.; Konstantakopoulou, O.; Galanis, P. Health Behavior Inventory-Short Form: Translation and Validation in Greek. *Arch Hell Med* **2026**, *Under press*.
28. Shapiro, G.K.; Tatar, O.; Dube, E.; Amsel, R.; Knauper, B.; Naz, A.; Perez, S.; Rosberger, Z. The Vaccine Hesitancy Scale: Psychometric Properties and Validation. *Vaccine* **2018**, *36*, 660–667, doi:10.1016/j.vaccine.2017.12.043.
29. Gialama, M.; Kleisiaris, C.; Malliarou, M.; Papagiannis, D.; Papathanasiou, I.V.; Karavasileiadou, S.; Almegewly, W.H.; Tsaras, K. Validity and Reliability of the Greek Version of Adult Vaccine Hesitancy Scale in Terms of Dispositional Optimism in a Community-Dwelling Population: A Cross-Sectional Study. *Healthcare* **2024**, *12*, 1460, doi:10.3390/healthcare12151460.
30. World Medical Association Declaration of Helsinki: Ethical Principles for Medical Research Involving Human Subjects. *JAMA* **2013**, *310*, 2191, doi:10.1001/jama.2013.281053.
31. Moisoglou, I.; Passali, C.; Tsiachri, M.; Galanis, P. Predictors of COVID-19 Vaccine Uptake in Teachers: An On-Line Survey in Greece. *J Community Health* **2023**, *48*, 59–66, doi:10.1007/s10900-022-01144-x.
32. Ortiz-Sánchez, E.; Velando-Soriano, A.; Pradas-Hernández, L.; Vargas-Román, K.; Gómez-Urquiza, J.L.; Cañadas-De la Fuente, G.A.; Albendín-García, L. Analysis of the Anti-Vaccine Movement in Social Networks: A Systematic Review. *International Journal of Environmental Research and Public Health* **2020**, *17*, 5394, doi:10.3390/ijerph17155394.
33. van der Linden, S. Misinformation: Susceptibility, Spread, and Interventions to Immunize the Public. *Nat Med* **2022**, *28*, 460–467, doi:10.1038/s41591-022-01713-6.
34. Rasul, M.E.; Ahmed, S. Not All Conservatives Are Vaccine Hesitant: Examining the Influence of Misinformation Exposure, Political Ideology, and Flu Vaccine Acceptance on COVID-19 Vaccine Hesitancy. *Vaccines* **2023**, *11*, 586, doi:10.3390/vaccines11030586.
35. Nan, X.; Wang, Y.; Thier, K. Why Do People Believe Health Misinformation and Who Is at Risk? A Systematic Review of Individual Differences in Susceptibility to Health Misinformation. *Social Science & Medicine* **2022**, *314*, 115398, doi:10.1016/j.socscimed.2022.115398.
36. Chandrasekaran, R.; T, M.S.; Moustakas, E. Racial and Demographic Disparities in Susceptibility to Health Misinformation on Social Media: National Survey-Based Analysis. *Journal of Medical Internet Research* **2024**, *26*, e55086, doi:10.2196/55086.

 doi:10.20944/preprints202601.0698.v1

37. Scherer, L.D.; McPhetres, J.; Pennycook, G.; Kempe, A.; Allen, L.A.; Knoepke, C.E.; Tate, C.E.; Matlock, D.D. Who Is Susceptible to Online Health Misinformation? A Test of Four Psychosocial Hypotheses. *Health Psychology* **2021**, *40*, 274–284, doi:10.1037/hea0000978.
38. Galanis, P.; Vraka, I.; Siskou, O.; Konstantakopoulou, O.; Katsiroumpa, A.; Moisoglou, I.; Kaitelidou, D. Cross-Sectional Assessment of Predictors for COVID-19 Vaccine Uptake: An Online Survey in Greece. *Vacunas* **2022**, *23*, S60–S66, doi:10.1016/j.vacun.2022.03.003.
39. Segado Fernández, S.; Jiménez Gómez, B.; Jiménez Hidalgo, P.; Lozano-Estevan, M.D.C.; Herrera Peco, I. Disinformation about Diet and Nutrition on Social Networks: A Review of the Literature. *Nutr Hosp* **2025**, *42*, 366–375, doi:10.20960/nh.05533.
40. Wang, R.; He, Y.; Xu, J.; Zhang, H. Fake News or Bad News? Toward an Emotion-Driven Cognitive Dissonance Model of Misinformation Diffusion. *Asian Journal of Communication* **2020**, *30*, 317–342, doi:10.1080/01292986.2020.1811737.
41. Ruani, M.A.; Reiss, M.J. Susceptibility to COVID-19 Nutrition Misinformation and Eating Behavior Change during Lockdowns: An International Web-Based Survey. *Nutrients* **2023**, *15*, 451, doi:10.3390/nu15020451.
42. Lee, J.J.; Kang, K.-A.; Wang, M.P.; Zhao, S.Z.; Wong, J.Y.H.; O'Connor, S.; Yang, S.C.; Shin, S. Associations Between COVID-19 Misinformation Exposure and Belief With COVID-19 Knowledge and Preventive Behaviors: Cross-Sectional Online Study. *J Med Internet Res* **2020**, *22*, e22205, doi:10.2196/22205.
43. Garcini, L.M.; Rosenfeld, J.; Kneese, G.; Bondurant, R.G.; Kanzler, K.E. Dealing with Distress from the COVID-19 Pandemic: Mental Health Stressors and Coping Strategies in Vulnerable Latinx Communities. *Health & Social Care in the Community* **2022**, *30*, 284–294, doi:10.1111/hsc.13402.
44. Dame Adjin-Tettey, T. Combating Fake News, Disinformation, and Misinformation: Experimental Evidence for Media Literacy Education. *Cogent Arts & Humanities* **2022**, *9*, 2037229, doi:10.1080/23311983.2022.2037229.
45. Redaelli, S.; Biller-Andorno, N.; Gloeckler, S.; Brown, J.; Spitale, G.; Germani, F. Mastering Critical Thinking Skills Is Strongly Associated with the Ability to Recognize Fakeness and Misinformation. *Front. Educ.* **2025**, *10*, doi:10.3389/feduc.2025.1577692.
46. Apuke, O.D.; Omar, B.; Asude Tunca, E. Literacy Concepts as an Intervention Strategy for Improving Fake News Knowledge, Detection Skills, and Curtailing the Tendency to Share Fake News in Nigeria. *Child & Youth Services* **2023**, *44*, 88–103, doi:10.1080/0145935X.2021.2024758.
47. Zou'bi, R.M.A. The Impact of Media and Information Literacy on Students' Acquisition of the Skills Needed to Detect Fake News. *Journal of Media Literacy Education* **2022**, *14*, 58–71.
48. McGrew, S.; Chinoy, I. Fighting Misinformation in College: Students Learn to Search and Evaluate Online Information through Flexible Modules. *Information and Learning Sciences* **2022**, *123*, 45–64, doi:10.1108/ILS-09-2021-0081.
49. Nygren, T.; Guath, M.; Axelsson, C.-A.W.; Frau-Meigs, D. Combatting Visual Fake News with a Professional Fact-Checking Tool in Education in France, Romania, Spain and Sweden. *Information* **2021**, *12*, 201, doi:10.3390/info12050201.