

Article

Who Should Bear the Responsibility for Combating Health Misinformation on Social Media? An Analysis of Sociodemographic Factors Using HINTS 6 Data

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Abstract

Background/Objectives: Health misinformation on social media is a growing public health concern, yet less is known about whom the public holds primarily responsible for reducing it. This study examined sociodemographic differences in U.S. adults' perceived responsibility for reducing health misinformation on social media. **Methods:** This cross-sectional study used nationally representative data from the Health Information National Trends Survey 6 (HINTS 6, 2022). Respondents were asked who has the main responsibility for reducing false or misleading health information on social media. Descriptive analyses reported unweighted counts and weighted percentages. Survey-weighted multinomial logistic regression with jackknife replicate variance estimation was used to examine associations with age, sex assigned at birth, race/ethnicity, education, marital status, full-time work status, and household income, and design-adjusted Wald tests assessed the overall association of each characteristic. **Results:** Among 6252 respondents, the largest weighted proportion attributed responsibility to social media platforms such as Facebook, Twitter, or YouTube (31.40%), followed by individual social media users (18.55%), the government (15.87%), medical providers and health care systems (13.79%), the news media (12.60%), and other sources (3.97%). In the adjusted model ($n = 5306$), age ($p = 0.032$) and education ($p = 0.014$) were associated with perceived responsibility overall. Compared with adults aged 65 years or older, adults aged 18–34 years had lower odds of naming platforms (AOR = 0.59, 95% CI: 0.41–0.85), the government (AOR = 0.57, 95% CI: 0.35–0.93), the news media (AOR = 0.48, 95% CI: 0.26–0.87), and medical providers and health care systems (AOR = 0.31, 95% CI: 0.19–0.52) rather than individual users, and adults aged 35–49 years showed a similar pattern. Adults with less than a high school education had higher odds than college graduates of selecting the government (AOR = 3.13, 95% CI: 1.45–6.76), the news media (AOR = 3.24, 95% CI: 1.15–9.14), and platforms (AOR = 2.12, 95% CI: 1.03–4.38). In sensitivity analyses, the direction of the main age and education estimates was broadly consistent; however, the overall age association was not statistically significant with an alternative age classification ($p = 0.321$) or among social media users only ($p = 0.071$). **Conclusions:** Perceived responsibility for reducing health misinformation on social media differs mainly by age and education, although statistical evidence for the age association depended on the age classification and the population analyzed. As a policy implication, the findings support a shared-responsibility approach involving platforms, public health agencies, health care systems, news media, and users; whether tailoring interventions to these sociodemographic differences improves their effectiveness should be tested in future studies.



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1. Introduction

Health misinformation on social media has become a significant public health concern [1]. Health misinformation, defined as health-related claims that contradict current scientific consensus, can adversely affect individuals' health behaviors and decisions [2]. During the COVID-19 pandemic, its rapid spread was significant enough that the World Health Organization and the United Nations called it an "infodemic" [3,4]. Much of the research that followed has asked who is exposed to health misinformation, who believes it, and who shares it [2,5]. A related question has received far less attention: whom the public holds responsible for reducing it. This question of responsibility attribution is the focus of the present study. Public views on responsibility matter because they may shape support for platform regulation, trust in institutional corrections, expectations of clinicians and health systems, and individuals' own willingness to verify or correct what they see online.

Judgments about who is responsible for a shared problem have long been studied in social psychology and media theory. Classic research on diffusion of responsibility shows that when many people or institutions could plausibly act, individuals tend to assume that someone else will act, so that personal responsibility feels smaller as the number of potential actors grows [6]. Health misinformation on social media fits this pattern well: platforms host the content, users share it, medical providers could correct it, government agencies could regulate it, and news outlets could fact-check it. Social responsibility theory of the press adds a related idea specific to media institutions: outlets that reach a mass audience have an obligation to inform the public accurately, not simply a right to publish freely [7]. Together, these two ideas suggest that perceived responsibility for reducing health misinformation is unlikely to be random. It may reflect how people place themselves and different institutions within a shared information system, and that placement may differ across social groups.

Public engagement with health information on social media has grown alongside the platforms themselves. Many adults now look for information about symptoms, treatments, and health news on social media rather than through traditional sources such as clinicians, printed materials, or official health websites [8]. This shift changes not only where people find health information but also how they judge whether it is accurate and whether to act on it. Because a single social media feed can mix content from health agencies, journalists, marketers, and ordinary users, it is often hard for a reader to tell who produced a given piece of health information or why it appeared on their screen. This blurred sense of authorship helps explain why responsibility for health misinformation is difficult to assign to any one actor.

The scale of social media adds to this difficulty. By January 2022, approximately 4.62 billion people, about 58% of the global population, used social media [8]. Social media can support health promotion and education, but it can also spread misleading content that leads to harmful health outcomes [4], and misinformation can spread faster than accurate health information can catch up [9]. Reducing health misinformation is further complicated by malicious actors who spread false content deliberately, by cultural or contextual factors that shape how people receive and act on it [10], and by political discourse that can reinforce it [11]. Under these conditions, no single actor controls the flow of health information, which is precisely the situation in which responsibility becomes diffuse.

Cancer illustrates what is at stake and also explains the data source used in this study. HINTS is administered by the National Cancer Institute, and cancer remains one of the leading topics of health information seeking among U.S. adults [12]. False claims about cancer treatment, prevention, and causes spread easily on social media, confusing people who are looking for reliable information and sometimes leading them toward harmful choices [13]. Research has shown that misinformation about alternative cancer treatments, such as unproven herbal remedies or conspiracy theories about mainstream treatments like chemotherapy, can lead to delayed diagnosis, poor treatment adherence, and adverse health outcomes [13]. The HINTS 6 survey revealed that cancer-related health misinformation disproportionately affects individuals with lower health literacy and those who rely heavily on social media for health information [14]. The responsibility item analyzed here, however, asks about health misinformation on social media in general rather than about cancer specifically; cancer is discussed as an example of the health consequences that make the question of responsibility practically important.

Research indicates that factors such as age, education level, and socioeconomic status are associated with susceptibility to health misinformation and the likelihood of sharing it [15]. Evidence on how the same factors relate to perceived responsibility for reducing health misinformation is much thinner. National descriptive estimates for the HINTS 6 responsibility item are available from the HINTS program [14], and a secondary analysis of the same survey by Galinkala and colleagues focused on age, using binary logistic regression models, and found that older adults were more likely to assign responsibility to medical providers and less likely to assign it to individual users [16]. What has not been examined is how the complete set of responsibility options relates, simultaneously, to a broader range of sociodemographic characteristics, including education, income, employment, and marital status, in a single model that treats the outcome as a choice among competing actors.

The aim of this study was to address this gap by examining whether sociodemographic characteristics are associated with U.S. adults' perceived responsibility for reducing health misinformation on social media. Specifically, it examined associations between perceived responsibility and age, sex assigned at birth, race/ethnicity, education level, marital status, employment status, and household income, using nationally representative data from the Health Information National Trends Survey [14]. The incremental contribution of this analysis is threefold: it models the complete multinomial responsibility outcome rather than selected binary contrasts, it examines a broader set of sociodemographic characteristics jointly, and it tests the overall association of each characteristic in addition to category-specific contrasts. The relevance of the question is underscored by HINTS 6 estimates showing that, among social media users, more than one-third (35.61%) believed that "a lot" of the health information they see on social media is false or misleading, and almost half (45.77%) believed that "some" of it is [15].

2. Materials and Methods

2.1. Study Design and Data Source

This study used a cross-sectional secondary analysis of publicly available data from the HINTS 6, administered by the National Cancer Institute (NCI). HINTS is a nationally representative survey that has been conducted since 2003 to assess the U.S. public's knowledge, attitudes, and behaviors related to cancer information, health communication, health information technology, and health-related decision-making [14]. The analysis used the HINTS 6 public-use dataset in R format (file `hints6_public.rda`, release dated 24 May 2024).

HINTS 6 data were collected from March to November 2022 using a mixed-mode design that included both web-based and paper survey options. The sampling frame was

provided by Marketing Systems Group and included four sampling strata: high-minority rural, low-minority rural, high-minority urban, and low-minority urban. Households received up to four mailings using a modified Dillman approach. One adult per household was selected using the next-birthday method. A \$2 incentive was provided with the survey mailing, and an additional \$10 incentive was offered to encourage web survey completion. HINTS 6 achieved a household response rate of 28.1% and included 6252 respondents, representing a weighted U.S. adult population of approximately 258.4 million. The public-use file provides a final full-sample person weight and 50 jackknife replicate weights. The full-sample weight was constructed by computing household base weights as the reciprocal of the probability of selection, adjusting them for household nonresponse within adjustment cells, multiplying them by the number of adults in the household to account for within-household selection, and calibrating (raking) the resulting person-level weights to 2021 American Community Survey control totals for age, gender, educational attainment, marital status, race, ethnicity, and census region, and to national estimates of health insurance coverage and of ever having been diagnosed with cancer. The replicate weights were created with the delete-one-group jackknife (JK1) method, with the weighting steps repeated within each replicate [17].

Although HINTS 7 data became available more recently, the HINTS 7 public codebook did not include the dependent variable of interest for this study: “Who do you think has the main responsibility for reducing the amount of false or misleading health information on social media?” Therefore, HINTS 6 was used because it was the most recent HINTS cycle that included this responsibility-attribution item.

2.2. Measures

The dependent variable was item B15 in Section B of the HINTS 6 questionnaire: “Who do you think has the main responsibility for reducing the amount of false or misleading health information on social media?” Response options were individual social media users; the news media; social media platforms like Facebook, Twitter, or YouTube; the government; medical providers and health care systems; and other (please specify). Because respondents were asked to name the actor with the main responsibility, the item captures relative attribution of primary responsibility to one actor rather than endorsement of responsibility shared among several actors. The substantive “other” category was retained as an outcome category in all regression models and was not used as the reference category. For descriptive analyses, missing responses (not ascertained or question never seen) and multiple responses selected in error were categorized as “Did Not Report” ($n = 258$). For the primary multinomial logistic regression analysis, “Did Not Report” responses were excluded because they did not represent a substantive belief regarding responsibility for reducing health misinformation on social media. A sensitivity analysis retained “Did Not Report” as a separate missing-response category to assess the robustness of the primary findings. According to the HINTS 6 codebook, item B15 was intended for respondents who use social media; however, most respondents who reported not using social media also answered it, and they were retained in the primary analysis, with a sensitivity analysis restricted to social media users.

Independent variables included age, sex assigned at birth, race and ethnicity, education, marital status, full-time work status, and household income. Age was categorized as 18–34, 35–49, 50–64, and 65 years or older, based on the HINTS age recode AgeGrpB with its two oldest categories (65–74 and 75 years or older) combined; these groupings follow conventional life-stage categories and yield intervals of comparable width for adults younger than 65 years. Results obtained with the alternative four-level HINTS recode AgeGrpA (18–34, 35–39, 40–44, and 45 years or older) are reported in Supplementary Table S6.

Only the categorical age variable was entered in the models; neither continuous age nor year of birth was included. Sex assigned at birth was categorized as male or female, based on the item asking for the sex on the respondent's original birth certificate. Race and ethnicity were categorized as non-Hispanic White, non-Hispanic Black or African American, Hispanic, non-Hispanic Asian, and non-Hispanic other race/ethnicity (hereafter, other race/ethnicity). Educational attainment was categorized as less than high school, high school graduate, some college, and college graduate or more. Marital status was categorized as married, living as married or with a romantic partner, divorced or widowed, and separated or single/never married. Full-time work status was categorized as yes or no. Household income was analyzed using the HINTS imputed income variable and categorized as \$0–\$19,999, \$20,000–\$49,999, \$50,000–\$99,999, and \$100,000 or more.

2.3. Statistical Analysis

All analyses accounted for the complex survey design of HINTS 6. Descriptive statistics were used to summarize the full sample ($N = 6252$) and the distribution of responses to the dependent variable. In the descriptive analysis, counts are unweighted, and percentages and 95% confidence intervals are weighted; the confidence intervals were computed from jackknife replicate variance estimates with a t distribution with 49 degrees of freedom, consistent with HINTS analytic guidance [18].

Multinomial logistic regression was used to examine associations between sociodemographic characteristics and perceived primary responsibility for reducing health misinformation on social media. The reference outcome category was “individual social media users.” Adjusted odds ratios (AORs) and 95% confidence intervals (CIs) were estimated for each non-reference outcome category: social media platforms, the government, medical providers and health care systems, the news media, and other. The model was adjusted for age, sex assigned at birth, race and ethnicity, education, marital status, full-time work status, and household income. Because the outcome is nominal, multinomial logistic regression was preferred over ordinal models, which assume an ordering of categories, and over separate binary models, which do not use the full outcome jointly. The assumptions of the model were addressed as follows. Observations were treated as independent conditional on the survey design, which was accounted for through replicate-weight variance estimation. The independence of irrelevant alternatives assumption was examined by re-estimating the model after removing one outcome category (“other”) and comparing the remaining coefficients; the Hausman–McFadden test was not used because it is not designed for replicate-weighted survey data. Multicollinearity among predictors was assessed with generalized variance inflation factors (GVIFs), scaled as $GVIF^*(1/(2 \cdot df))$ to make predictors with different numbers of categories comparable [19]. Linearity in the logit did not need to be assessed because all predictors were categorical, and sparse outcome-by-predictor cells were examined as part of the model diagnostics.

Reference categories were selected based on interpretability and sample distribution. The reference groups were age 65 years or older, female sex, other race/ethnicity, college graduate or more, separated or single/never married, not working full time, and household income of \$100,000 or more. For each predictor, the overall association with the outcome was tested with a design-adjusted Wald F test of the joint null hypothesis that all coefficients for that predictor were zero across the five outcome equations [20]. Because the model yields 90 category-specific contrasts, the analysis was treated as exploratory: no formal correction for multiple comparisons was applied [21], and interpretation emphasized the magnitude and precision of the AORs and their 95% CIs, together with the global Wald tests, rather than statistical significance alone. Statistical significance was assessed using

two-sided p -values, with $p < 0.05$ considered statistically significant; category-specific contrasts for predictors without a significant global test are described as exploratory.

The primary regression analysis excluded respondents coded as “Did Not Report” for the dependent variable or any predictor because this category represented item nonresponse rather than a substantive response category. Of the 6252 respondents, 946 (15.1% unweighted; 14.0% weighted) were excluded: 258 had no substantive response to the dependent variable, and a further 688 had a substantive response but were missing at least one predictor. Item nonresponse was most common for race and ethnicity ($n = 687$), marital status ($n = 415$), full-time work status ($n = 412$), sex ($n = 410$), and education ($n = 404$), and was uncommon for age ($n = 98$) and household income ($n = 17$), the latter because HINTS provides an imputed income variable. Missingness clustered within respondents: 382 of the excluded respondents were missing five or more of the eight model variables. The analytic sample therefore comprised 5306 respondents. To assess potential selection bias, the weighted distribution of each variable was compared between included and excluded respondents using design-adjusted Wald F tests. A sensitivity analysis was also conducted by retaining “Did Not Report” as a separate missing-response category for the dependent variable and predictors. The results of the sensitivity analysis were compared with the primary model to assess whether the direction and statistical significance of the substantive associations changed.

Model diagnostics were evaluated for the primary and all sensitivity analyses. Diagnostics included model convergence, number of failed replicate-weight models, condition number (the ratio of the largest to the smallest singular value of the model design matrix), sparse-cell patterns, extreme adjusted odds ratios (AOR > 20 or < 0.05), and very wide confidence intervals (ratio of the upper to the lower confidence limit > 1000). These diagnostics were used to assess model stability and to determine whether the primary or sensitivity model should be emphasized in the manuscript. Because the primary model demonstrated stable diagnostics and the sensitivity model produced additional unstable estimates involving “Did Not Report” categories, the complete-response primary model was retained as the main analytic model.

Four further sensitivity analyses were conducted: (i) excluding the “other” outcome category, to assess the stability of the relative odds among the predefined actors; (ii) omitting household income, to evaluate whether adjustment for income attenuated or masked an association between full-time work status and perceived responsibility; (iii) using the HINTS AgeGrpA age categories; and (iv) restricting the analytic sample to respondents who reported using social media.

All analyses were performed using R version 4.5.1 (R Foundation for Statistical Computing, Vienna, Austria) [22]. Survey-weighted descriptive estimates used the survey package [23], with a replicate-weight design specified from the HINTS 6 full-sample weight (PERSON_FINWT0) and the 50 replicate weights (PERSON_FINWT1–PERSON_FINWT50), jackknife type JK1, and a jackknife coefficient of 0.98 (49/50). Multinomial logistic regression models were fitted with the multinom() function of the nnet package [24], with weights rescaled to a mean of one. Each model was fitted once with the full-sample weight to obtain the point estimates and once with each of the 50 replicate weights; the jackknife variance-covariance matrix of the coefficients was calculated as $0.98 \times \Sigma(\beta_r - \beta)(\beta_r - \beta)^T$, where β_r is the vector of estimates from replicate r and β the full-sample estimate. The 95% CIs and two-sided p -values were based on a t distribution with 49 degrees of freedom, and the design-adjusted Wald F statistic for q coefficients was computed as $(W/q) \times (49 - q + 1)/49$ with q and $49 - q + 1$ degrees of freedom [18]. GVIFs were computed from the weighted correlation matrix of the dummy-coded predictors. The analytic code, including variable recoding, survey-weight specification, regression mod-

els, sensitivity analyses, diagnostics, and table generation, is publicly available (see Data Availability Statement).

2.4. Ethical Considerations

This study used publicly available, de-identified HINTS 6 data.

3. Results

3.1. Descriptive Statistics

Table 1 presents the descriptive characteristics of the full sample. Nearly one-third of respondents (31.40%) attributed the main responsibility for reducing health misinformation on social media to the platforms themselves. Fewer than one in five named individual users (18.55%), followed by the government (15.87%), medical providers and health care systems (13.79%), and the news media (12.60%); 3.97% named another actor and 3.81% did not report a substantive response. Adults aged 65 years or older made up about one-fifth of the weighted sample (21.32%), and each of the three younger age groups accounted for about one-quarter. Females accounted for 47.36% and non-Hispanic White adults for 55.35% of the sample. More than one-third (36.10%) had some college education, and nearly half (47.49%) were married. Just over half (50.85%) worked full time, and 30.05% had household incomes of \$50,000 to \$99,999.

Table 1. Descriptive characteristics of the full HINTS 6 sample (N = 6252).

Variables	Unweighted <i>n</i> (% Weighted ¹)	Weighted 95% CI
Dependent variable		
Who do you think has the main responsibility for reducing the amount of false or misleading health information on social media?		
Individual Social Media Users	1102 (18.55)	16.95–20.15
The News Media	763 (12.60)	11.06–14.15
Social Media Platforms (e.g., Facebook, Twitter, or YouTube)	2040 (31.40)	29.58–33.22
The Government	923 (15.87)	13.99–17.74
Medical Providers and Health Care Systems	896 (13.79)	12.09–15.50
Other	270 (3.97)	3.10–4.85
Did Not Report	258 (3.81)	3.00–4.63
Independent variables		
Age		
18–34	939 (25.62)	23.99–27.24
35–49	1240 (24.97)	23.25–26.69
50–64	1772 (26.95)	25.71–28.20
65+	2203 (21.32)	21.13–21.52
Did Not Report	98 (1.13)	0.75–1.52
Sex Assigned at Birth		
Male	2307 (45.93)	45.10–46.76
Female	3535 (47.36)	46.62–48.10
Did Not Report	410 (6.71)	5.63–7.79

Table 1. Cont.

Variables	Unweighted <i>n</i> (% Weighted ¹)	Weighted 95% CI
Race and Ethnicity		
Non-Hispanic White	3203 (55.35)	54.41–56.30
Non-Hispanic Black or African American	889 (9.94)	9.62–10.25
Hispanic	1001 (15.42)	15.03–15.80
Non-Hispanic Asian	288 (5.17)	4.81–5.53
Other Race/Ethnicity	184 (4.56)	4.32–4.80
Did Not Report	687 (9.56)	8.32–10.80
Education		
Less than High School	387 (6.36)	5.13–7.59
High School Graduate	1068 (20.06)	18.33–21.79
Some College	1672 (36.10)	34.87–37.32
College Graduate or More	2721 (30.29)	29.93–30.65
Did Not Report	404 (7.19)	5.88–8.50
Marital Status		
Married	2624 (47.49)	46.70–48.27
Living as Married or Living With a Romantic Partner	373 (4.64)	4.09–5.20
Divorced or Widowed	1585 (10.66)	10.08–11.24
Separated or Single, Never Been Married	1255 (30.45)	29.56–31.34
Did Not Report	415 (6.76)	5.66–7.86
Work Full Time		
Yes	2778 (50.85)	48.61–53.08
No	3062 (42.32)	39.90–44.73
Did Not Report	412 (6.84)	5.77–7.90
Income Range		
\$0 to \$19,999	1210 (16.86)	15.26–18.46
\$20,000 to \$49,999	1646 (22.63)	20.68–24.58
\$50,000 to \$99,999	1780 (30.05)	28.12–31.97
\$100,000 or more	1599 (29.74)	27.76–31.73
Did Not Report	17 (0.72)	0.32–1.76

Abbreviations: CI—confidence interval. ¹ Counts are unweighted; percentages and 95% CIs are weighted using the HINTS 6 full-sample weight and 50 jackknife replicate weights (t distribution, 49 degrees of freedom). Percentages may not add up to 100% due to rounding. “Did Not Report” includes item nonresponse and multiple responses selected in error.

The regression analyses included 5306 respondents with complete data (Supplementary Table S1). Compared with included respondents, excluded respondents were older, less educated, less often married, less often employed full time, and had lower household incomes (all design-adjusted $p \leq 0.001$). However, among respondents who answered the dependent variable, the distribution of perceived responsibility did not differ significantly between those included and those excluded because of missing predictor data ($F(5,45) = 0.92, p = 0.476$).

3.2. Multinomial Logistic Regression Analysis Results

Table 2 presents the adjusted multinomial logistic regression results for factors associated with U.S. adults' perceived primary responsibility for reducing health misinformation on social media. The reference outcome category was "individual social media users," so each AOR compares the odds of naming a given actor, rather than individual users, as mainly responsible. After controlling for all other characteristics, age ($F(15,35) = 2.14$, $p = 0.032$) and education ($F(15,35) = 2.46$, $p = 0.014$) were associated with perceived responsibility overall (Table 3). No statistically significant overall association was detected for sex ($p = 0.216$), race and ethnicity ($p = 0.576$), marital status ($p = 0.329$), full-time work status ($p = 0.632$), or household income ($p = 0.690$).

Table 2. Multivariable multinomial logistic regression analysis of factors associated with perceived main responsibility for reducing the amount of false or misleading health information on social media ($n = 5306$).

Variable	Social Media Platforms	The Government	Medical Providers and Health Care Systems	The News Media	Other
Age (Ref. 65+)					
18–34	0.59 (0.41–0.85) **	0.57 (0.35–0.93) *	0.31 (0.19–0.52) ***	0.48 (0.26–0.87) *	0.67 (0.32–1.41)
35–49	0.57 (0.39–0.85) **	0.49 (0.32–0.75) **	0.28 (0.16–0.49) ***	0.39 (0.24–0.64) ***	0.92 (0.42–2.03)
50–64	0.72 (0.50–1.03)	0.74 (0.47–1.18)	0.51 (0.32–0.81) **	0.57 (0.36–0.91) *	1.31 (0.61–2.80)
Sex Assigned at Birth (Ref. Female)					
Male	0.85 (0.63–1.14)	1.11 (0.81–1.54)	0.78 (0.55–1.11)	0.87 (0.58–1.30)	1.70 (0.87–3.32)
Race and Ethnicity (Ref. Other Race/Ethnicity)					
White	1.34 (0.62–2.86)	0.67 (0.26–1.70)	1.00 (0.41–2.47)	0.87 (0.41–1.82)	0.70 (0.23–2.13)
Black or AA	1.37 (0.61–3.08)	0.97 (0.33–2.87)	1.22 (0.46–3.28)	1.01 (0.45–2.26)	0.49 (0.15–1.58)
Hispanic	1.32 (0.54–3.23)	1.07 (0.34–3.39)	0.84 (0.30–2.34)	1.07 (0.47–2.42)	0.80 (0.23–2.77)
Asian	1.54 (0.52–4.53)	1.64 (0.48–5.60)	1.44 (0.14–15.06)	0.95 (0.37–2.46)	0.20 (0.02–2.35)
Education (Ref. College Graduate or More)					
Less than HS	2.12 (1.03–4.38) *	3.13 (1.45–6.76) **	1.71 (0.52–5.61)	3.24 (1.15–9.14) *	1.12 (0.29–4.33)
HS Graduate	1.40 (0.93–2.11)	1.90 (1.19–3.03) **	1.71 (0.99–2.97)	2.50 (1.37–4.55) **	0.93 (0.33–2.59)
Some College	0.80 (0.58–1.09)	1.24 (0.79–1.95)	1.24 (0.76–2.00)	1.33 (0.80–2.22)	0.61 (0.36–1.04)
Marital Status (Ref. Separated or Single, Never Been Married)					
Married	0.78 (0.57–1.06)	0.74 (0.46–1.18)	0.65 (0.45–0.94) *	0.78 (0.50–1.24)	0.42 (0.19–0.94) *
LA Married/WRP	1.72 (0.98–3.04)	1.45 (0.72–2.91)	1.00 (0.47–2.12)	1.60 (0.78–3.27)	2.43 (0.76–7.78)
Divorced/Widowed	0.86 (0.59–1.24)	0.71 (0.44–1.13)	0.64 (0.41–1.02)	0.77 (0.49–1.23)	0.78 (0.41–1.50)
Work Full Time (Ref. No)					
Yes	0.89 (0.63–1.26)	1.04 (0.70–1.54)	0.83 (0.53–1.29)	1.04 (0.70–1.56)	0.59 (0.29–1.21)
Income Range (Ref. \$100,000 or more)					
\$0 to \$19,999	1.15 (0.65–2.05)	1.60 (0.79–3.22)	1.49 (0.78–2.86)	2.20 (1.06–4.54) *	1.04 (0.31–3.49)
\$20,000 to \$49,999	1.30 (0.88–1.91)	1.39 (0.72–2.67)	1.40 (0.82–2.38)	1.45 (0.82–2.56)	1.50 (0.88–2.58)
\$50,000 to \$99,999	1.31 (0.96–1.80)	1.15 (0.73–1.80)	1.53 (0.93–2.50)	1.15 (0.72–1.85)	1.00 (0.55–1.83)

Values are adjusted odds ratios (95% confidence intervals). The reference outcome category is individual social media users. Confidence intervals and p -values were based on jackknife replicate variance estimates (50 replicate weights) and a t distribution with 49 degrees of freedom. Abbreviations: AA—African American; HS—high school; LA—living as; Ref.—reference; WRP—with romantic partner. * p -value < 0.05; ** p -value < 0.01; *** p -value < 0.001.

Table 3. Overall association of each sociodemographic characteristic with perceived main responsibility (design-adjusted Wald F tests) and collinearity diagnostics ($n = 5306$).

Characteristic	Wald F (df1, df2)	<i>p</i> -Value	Scaled GVIF
Age	2.14 (15, 35)	0.032	1.11
Sex assigned at birth	1.48 (5, 45)	0.216	1.03
Race and ethnicity	0.91 (20, 30)	0.576	1.02
Education	2.46 (15, 35)	0.014	1.05
Marital status	1.18 (15, 35)	0.329	1.09
Full-time work status	0.69 (5, 45)	0.632	1.18
Household income	0.78 (15, 35)	0.690	1.08

Age showed the clearest pattern. Compared with adults aged 65 years or older, adults aged 18–34 and 35–49 years had lower odds of naming each institutional actor, rather than individual users, as mainly responsible. For adults aged 18–34 years, the odds were 41% lower for social media platforms (AOR = 0.59, 95% CI: 0.41–0.85), 43% lower for the government (AOR = 0.57, 95% CI: 0.35–0.93), about half for the news media (AOR = 0.48, 95% CI: 0.26–0.87), and 69% lower for medical providers and health care systems (AOR = 0.31, 95% CI: 0.19–0.52). Adults aged 35–49 years showed a similar pattern (platforms: AOR = 0.57, 95% CI: 0.39–0.85; government: AOR = 0.49, 95% CI: 0.32–0.75; news media: AOR = 0.39, 95% CI: 0.24–0.64; medical providers and health care systems: AOR = 0.28, 95% CI: 0.16–0.49). Adults aged 50–64 years had lower odds of naming medical providers and health care systems (AOR = 0.51, 95% CI: 0.32–0.81) and the news media (AOR = 0.57, 95% CI: 0.36–0.91), whereas their estimates for platforms and the government did not reach statistical significance. No statistically significant age difference was detected for naming another actor. Relative to the oldest adults, respondents younger than 50 years were more likely to place the main responsibility on individual users than on any institution.

Education was the second characteristic with a significant overall association. Compared with college graduates, adults with less than a high school education had about three times the odds of naming the government (AOR = 3.13, 95% CI: 1.45–6.76) or the news media (AOR = 3.24, 95% CI: 1.15–9.14), and about twice the odds of naming social media platforms (AOR = 2.12, 95% CI: 1.03–4.38), rather than individual social media users. High school graduates also had higher odds of naming the government (AOR = 1.90, 95% CI: 1.19–3.03) and the news media (AOR = 2.50, 95% CI: 1.37–4.55). The confidence intervals for adults with less than a high school education were wide, reflecting the small size of this group, and the lower limit for platforms was close to one.

No statistically significant overall association was detected for marital status or household income, although three category-specific contrasts had 95% CIs that excluded one; these are reported as exploratory. Compared with adults who were separated or single and had never been married, married adults had lower odds of naming medical providers and health care systems (AOR = 0.65, 95% CI: 0.45–0.94) or another actor (AOR = 0.42, 95% CI: 0.19–0.94) rather than individual social media users. Adults with an annual household income of \$0 to \$19,999 had higher odds than those with an income of \$100,000 or more of naming the news media (AOR = 2.20, 95% CI: 1.06–4.54).

No statistically significant overall association was detected for full-time work status (global $p = 0.632$); for example, the AOR for medical providers and health care systems was 0.83 (95% CI: 0.53–1.29). Likewise, no statistically significant overall association was detected for sex or for race and ethnicity in the adjusted model.

Collinearity among the predictors was low: all scaled GVIFs were below 1.2 (range 1.02–1.18; Table 3). Removing household income from the model (Supplementary Table S2)

changed the full-time work estimates only slightly (medical providers and health care systems: AOR = 0.81, 95% CI: 0.52–1.25), indicating that adjustment for income did not mask an association between employment and perceived responsibility. Without income in the model, the education AORs became larger (for example, less than high school vs. college graduate, news media: AOR = 4.37, 95% CI: 1.86–10.31), consistent with income accounting for part of the education gradient.

A sensitivity analysis retaining “Did Not Report” as a separate missing-response category is presented in Supplementary Table S3. In this model, 17 of the 18 statistically significant substantive contrasts in the primary model remained significant with the same direction; the remaining contrast (less than high school education, social media platforms) was of similar size but narrowly lost significance (AOR = 1.96, 95% CI: 1.00–3.85). Two additional substantive contrasts reached significance: high school graduates for medical providers and health care systems (AOR = 1.76, 95% CI: 1.05–2.97) and household income of \$50,000 to \$99,999 for platforms (AOR = 1.40, 95% CI: 1.03–1.89). However, the sensitivity model was less reliable overall: estimates involving “Did Not Report” categories were unstable, with 7 extreme odds ratios and 15 very wide confidence intervals, compared with none in the primary model (Supplementary Table S4). Therefore, the primary complete-response model excluding “Did Not Report” responses was retained as the main analysis. Excluding the “other” outcome category (Supplementary Table S5) left all 17 comparable significant contrasts unchanged in direction and significance, and the AORs changed by less than 5%. Using the HINTS AgeGrpA categories (Supplementary Table S6) reproduced the education findings but, because all adults aged 45 years or older formed one reference group, did not detect the broader age pattern; with this coarser age adjustment, full-time workers appeared to have lower odds of naming medical providers and health care systems (AOR = 0.63, 95% CI: 0.43–0.92). Restricting the analysis to social media users ($n = 4315$; Supplementary Table S7) produced AORs in the same direction for all 18 significant contrasts, 13 of which remained statistically significant in this smaller sample. The overall (global) tests, however, did not support the age association uniformly. The global age test remained significant when “Did Not Report” was retained ($p = 0.026$), when the “other” outcome was excluded ($p = 0.009$), and when income was omitted ($p = 0.020$). It was not significant with the AgeGrpA categories ($F(15,35) = 1.19, p = 0.321$) or among social media users only ($F(15,35) = 1.82, p = 0.071$). The global education test remained significant in all sensitivity analyses ($p \leq 0.046$). Thus, the direction of the age and education estimates was broadly consistent across sensitivity analyses, but the statistical evidence for an overall age association depended on the age classification and the population analyzed.

The Wald F test evaluates the joint null hypothesis that all coefficients for a characteristic are zero across the five outcome equations; $F = (W/q) \times (49 - q + 1)/49$, where W is the Wald statistic based on the jackknife variance–covariance matrix and q the number of coefficients tested. GVIF is the generalized variance inflation factor, scaled as $GVIF^{1/(2 \cdot df)}$, where df is the number of dummy variables for the characteristic.

4. Discussion

This study examined how sociodemographic characteristics are associated with U.S. adults’ perceived primary responsibility for reducing health misinformation on social media. Using nationally representative HINTS 6 data, it extends earlier work in two ways: it models the complete set of responsibility options jointly rather than as separate binary contrasts, and it examines a broader set of sociodemographic characteristics, including education, income, employment, and marital status, alongside age [16]. Two characteristics, age and education, were associated with perceived responsibility overall in the primary model, although the overall age association was not statistically significant in every sensi-

tivity analysis; the remaining associations were isolated contrasts that should be regarded as exploratory.

The descriptive results showed that the largest proportion of U.S. adults attributed primary responsibility to social media platforms, followed by individual social media users, government entities, medical providers and health care systems, and the news media. Because the item asked respondents to name the actor with the main responsibility, these results describe how primary responsibility is distributed across the population, not whether respondents consider responsibility to be shared. This pattern suggests that many adults may not view health misinformation as only a matter of individual failure to identify inaccurate information. Rather, many adults appear to recognize that misinformation circulates within a broader digital information ecosystem shaped by platform design, algorithmic amplification, content moderation policies, and institutional communication. This interpretation is consistent with prior research showing that social media health misinformation is a public health problem requiring coordinated responses across platforms, government agencies, health systems, professional communicators, and users [3,5,9,10,25–28].

Age was the characteristic most clearly associated with perceived responsibility. Relative to adults aged 65 years or older, adults younger than 50 years had lower odds of naming any institutional actor, whether platforms, government, news media, or medical providers and health care systems, rather than individual users, and adults aged 50–64 years had lower odds for medical providers and health care systems and for the news media. The pattern was not a strictly linear gradient: the estimates for adults aged 18–34 and 35–49 years were similar, and those for adults aged 50–64 years were intermediate. This finding is consistent with the age-focused analysis of the same survey by Galinkala and colleagues, who found that older adults were more likely to assign responsibility to medical providers and less likely to assign it to individual users [16], and the multinomial model shows that the age difference extends to platforms, government, and news media as well. One possible explanation, which was not tested directly, is that younger adults have greater familiarity with social media as a user-driven environment and may therefore regard users as the first line of defense. Another possible explanation is that younger adults may encounter health content in more decentralized, peer-driven, or influencer-driven spaces, where medical providers are not perceived as the dominant gatekeepers of information. Prior research has shown that social media users frequently encounter health misinformation in everyday digital environments and that younger users may engage with platform-based health content in ways that differ from older adults [25,29,30]. Older adults, who use social media less often and tend to have more frequent contact with health professionals, may expect institutions to protect them from misleading content; because social media use and health care contact were not included in the models, these explanations remain possibilities that require further study. The age estimates had the same direction when the analysis was restricted to social media users, which suggests that the age pattern is not explained solely by older non-users answering the item. However, the overall age association did not reach statistical significance in this smaller sample ($p = 0.071$) or with the coarser AgeGrpA classification ($p = 0.321$). The age finding should therefore be regarded as consistent in direction but sensitive to the age specification and to the population analyzed, and it warrants confirmation in future surveys. The present findings extend the literature by showing that age differences are not limited to misinformation exposure or vulnerability; they also extend to perceived responsibility for correcting the problem.

Education was the other characteristic with a significant overall association and showed the most consistent pattern across actors. Compared with adults with a college degree or higher, adults with less than a high school education had higher odds of assigning responsibility to social media platforms, the government, and the news media rather than

to individual social media users. High school graduates also had higher odds of assigning responsibility to the government and the news media. These findings suggest that lower educational attainment is associated with a stronger tendency to assign responsibility to institutional or media actors rather than to individual users. This pattern may reflect differences in digital health literacy, confidence in evaluating online claims, perceived control over the information environment, or expectations that institutions should protect the public from misleading content, none of which were measured in this study. Prior studies have shown that education is associated with susceptibility to health misinformation, credibility judgments, and misinformation-sharing behavior [2,15,31]. The present study adds that education is also associated with the perceived locus of responsibility for reducing misinformation. The education gradient was larger when income was omitted from the model, which suggests that part of it reflects socioeconomic position more broadly. This distinction matters because interventions that focus only on individual media literacy may not fully address the expectations of groups who perceive misinformation as a problem requiring institutional accountability.

The association between lower educational attainment and attribution of responsibility to the news media deserves particular attention. Adults with less than a high school education and high school graduates had higher odds of selecting the news media rather than individual users as the responsible actor. One possible explanation is the blurred boundary between social media, news media, and digital information channels. Many users encounter news content through social media feeds rather than through traditional news platforms, making it difficult to distinguish whether misleading information is produced by news outlets, amplified by platforms, or shared by users. If confirmed, this would suggest that misinformation interventions should not treat social media literacy and news literacy as separate domains, and that public health communication strategies should help users evaluate the source, evidence base, and pathway of health information across hybrid media environments.

Married adults had lower odds than separated or single adults of naming medical providers and health care systems or another actor rather than individual social media users. Because no statistically significant overall association was detected for marital status in the global test, these contrasts may reflect chance findings among the many comparisons in the model and should be interpreted as exploratory. One possible explanation, which requires further study, is that married adults discuss health information within close interpersonal networks and therefore place relatively greater responsibility on individuals to evaluate and manage the information they share. The study did not measure household communication patterns, family health decision-making, or interpersonal correction of misinformation.

No statistically significant overall association was detected for full-time employment after adjustment for age. With a coarser age classification that combined all adults aged 45 years or older, full-time workers appeared to have lower odds of naming medical providers and health care systems; this apparent association was no longer observed once adults aged 65 years or older, fewer than one in five of whom worked full time, were distinguished from middle-aged adults. This pattern is consistent with possible residual confounding by age in the coarser specification, although the comparison cannot establish it. Omitting household income from the model did not materially change the employment estimates, which suggests that adjustment for income did not mask an association with employment.

Lower household income was associated with higher odds of naming the news media rather than individual users, but no statistically significant overall association was detected for income, and this single contrast should be interpreted cautiously. If confirmed, it could reflect socioeconomic differences in trust, media consumption, perceived institutional

accountability, or exposure to low-quality information environments. Recent research has emphasized that health misinformation can deepen existing inequalities by interacting with health literacy, trust, access to care, and social disadvantage [2,9,15,25,32]. We may surmise that individual-level correction of misinformation requires time, skills, and resources that are not equally distributed, but this mechanism was not measured in the present study.

Notably, no statistically significant association was detected for sex or race/ethnicity in the primary adjusted model, either in the global tests or in any category-specific contrast. This does not mean that sex or racial/ethnic differences are irrelevant to health misinformation. Prior studies have documented racial, ethnic, and demographic disparities in misinformation exposure, trust, and susceptibility [15,25,32]. Rather, the present findings suggest that when the outcome is specifically framed as responsibility attribution, age and education may be more salient correlates than sex or race/ethnicity in this dataset. Because the global Wald test does not depend on the choice of reference category, the absence of a significant association for race/ethnicity is not an artifact of using the small other race/ethnicity group as the reference. This is an important empirical distinction because factors associated with exposure to misinformation are not necessarily the same as factors associated with beliefs about who should correct misinformation.

Health misinformation is a persistent and serious challenge because sensational content can spread quickly to large audiences. It erodes trust in health care systems and affects vulnerable populations the most, widening existing health disparities [33]. New technologies bring additional challenges, including AI-driven infodemics, bots that spread deepfakes, and algorithms manipulated to favor partisan content [26]. Farukuoye and colleagues argue that one of the ways to effectively manage infodemics is through proactive collaboration across various stakeholders [34].

Generative artificial intelligence (AI) adds a further dimension that HINTS 6 could not capture. Tools that produce summarized answers instead of simple lists of links blur the line between hosting content and authoring it: in May 2026, the Munich Regional Court ruled that Google could be held directly liable for false statements produced by its AI Overview feature [35], and research on AI-assisted clinical decision-making shows that responsibility can become unclear when a system, its developers, and a clinician all shape a decision [36]. Because HINTS 6 was collected in 2022, before generative AI search summaries became widely used, its response options did not distinguish AI systems from other actors, and future surveys should ask about responsibility for AI-generated health information separately.

The present findings are specific to health information. Survey evidence from outside the health domain shows that, across several countries, most adults say that social media platforms, rather than governments, should be primarily responsible for moderating false or harmful content in general, which matches the present study's finding that platforms received the largest share of responsibility attributions [37]; for generative AI tools, however, preferences shift toward government oversight in some countries [37]. Because HINTS 6 asked only about health information, this study cannot test whether the sociodemographic patterns observed here also apply to non-health misinformation, and future surveys that ask the same responsibility-attribution question across topics would help clarify this.

The findings suggest that efforts to reduce health misinformation on social media should move beyond individual-level media literacy alone. Because many adults attributed responsibility to social media platforms, platform-level interventions remain essential, including transparent content moderation, clearer labeling of disputed health claims, algorithmic accountability, and stronger collaboration with public health agencies. At the same time, the association between lower educational attainment and greater attribution of responsibility to platforms, government, and the news media suggests that misinforma-

tion interventions may need to take educational background into account, although this study did not evaluate interventions. Plain-language communication, source-verification guidance, and practical examples of how to evaluate health claims may be particularly important, but these strategies should avoid implying that misinformation susceptibility is simply an individual failure.

The findings are also compatible with a broader shared-responsibility model, which we propose as a policy implication rather than as a conclusion demonstrated by the survey item, since respondents were asked to name a single actor with the main responsibility. Health care systems can contribute through proactive patient education, brief discussions about online health information during clinical encounters, and referral to trusted digital resources. News media also remain important, particularly because lower education and, in an exploratory contrast, lower income were associated with greater attribution of responsibility to the news media. Public health agencies could therefore strengthen partnerships with journalists and media organizations to improve the accuracy, clarity, and timeliness of health reporting. Finally, the age differences suggest a hypothesis for future intervention research: because younger adults more often assign primary responsibility to individual users, approaches that build users' own verification skills through platform-native and peer-based formats may resonate with them, whereas older adults, who more often look to institutions, may be more receptive to messages delivered through health professionals, public health agencies, and trusted community sources. Whether such tailoring improves effectiveness was not assessed in this study and should be tested.

Several limitations of the present study should be considered. The cross-sectional design precludes causal inferences, and the associations reported here should not be interpreted as effects of sociodemographic characteristics. Self-reported data may be subject to measurement error or social desirability bias. The outcome was a single forced-choice item about the main responsible actor, so it could not capture beliefs that responsibility should be shared or graded across actors. Categorization of age groups and other sociodemographic variables may not capture nuanced differences within these categories, and small groups, such as adults with less than a high school education and some racial and ethnic groups, yielded imprecise estimates. The complete-response analysis excluded 14.0% of the weighted sample, and excluded respondents differed from included respondents in age, education, marital status, employment, and income; although the distribution of the outcome did not differ significantly between the two groups and the sensitivity analysis retaining nonresponse produced similar findings, selection bias cannot be ruled out if missingness was related to responsibility attribution. The model generated many category-specific contrasts, and some statistically significant contrasts may be chance findings; this is why the analysis was treated as exploratory and emphasized the global tests and the precision of the estimates. In addition, the overall age association was sensitive to the age classification and to restriction to social media users, so the age finding should be confirmed in future studies. The response rate of 28.1% also raises concerns about potential nonresponse bias, which could affect the generalizability of the findings, although the survey weights are designed to reduce it. In addition, HINTS 6 data were collected in 2022, before generative AI tools became a common source of online health information, so this survey could not measure responsibility attribution for AI-generated content separately from other social media content; this is an important direction for future HINTS cycles and other national surveys.

5. Conclusions

This study provides nationally representative evidence that U.S. adults' perceived responsibility for reducing health misinformation on social media differs by age and

education. Adults younger than 50 years were more likely than those aged 65 years or older to place the main responsibility on individual users rather than on platforms, the government, the news media, or medical providers and health care systems, and adults with lower educational attainment were more likely than college graduates to assign responsibility to the government, the news media, and social media platforms rather than to individual users. Associations with marital status and income were limited to single contrasts and should be considered exploratory, and no statistically significant overall association was detected for full-time work status, sex, or race/ethnicity. The direction of the age and education estimates was broadly consistent across sensitivity analyses, but the overall age association was not statistically significant in all of them.

These findings add to the existing literature by showing that perceived responsibility for health misinformation is socially patterned, particularly by age and education, rather than uniform across the population. As a policy implication, we propose that responses to health misinformation combine the efforts of platforms, public health agencies, health care systems, news media, and users rather than relying on generic media literacy campaigns alone. Whether tailoring misinformation-reduction strategies to differences in age and education improves their relevance, acceptability, and equity impact should be evaluated in future intervention studies.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/soc16110364/s1>, Table S1: Derivation of the analytic sample, item nonresponse, and comparison of included and excluded respondents ($n = 6252$); Table S2: Sensitivity analysis omitting household income ($n = 5306$); Table S3: Sensitivity adjusted multinomial logistic regression analysis including “Did Not Report” responses ($n = 6252$); Table S4: Model diagnostics and sparse-cell diagnostics; Table S5: Sensitivity analysis excluding the “other” outcome category ($n = 5076$); Table S6: Sensitivity analysis using the HINTS AgeGrpA age categories ($n = 5306$); Table S7: Sensitivity analysis restricted to respondents who reported using social media ($n = 4315$)

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