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Determinants of American adults' use of digital health and willingness to share health data to providers, family, and social media

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Abstract

With the global pandemic driving the adoption of digital health, understanding predictors or determinants of digital health usage and information sharing gives an opportunity to advocate for broader adoption. We examined the prevalence and predictors of digital health usage and information sharing behaviors among American adults. Data were from the Health Information National Trends Survey 5 Cycle 4. More than two-thirds used a digital resource for health-related activities (e.g., to check test results). About 81% were willing to share their digital data with their provider, 75% with family and 58% with friends. Only 14% shared health information on social media. Gender, education, device types, and performance expectancy of digital health were common factors associated with both digital health usage and information sharing behaviors. Other predictors included rurality, patient portal access, income, and having a chronic disease. Of note, we found that Asian American Pacific Islanders compared to whites were less likely to share information with providers. Performance expectancy was a significant determinant of information sharing. Those diagnosed with diabetes were 4% less likely to share information with their providers. With the growing digital divide, there is a need to advocate for more usable and accessible digital health to assist with person-centered care.

Keywords

Mobile Health; Digital Divide; Information Sharing; Culturally Appropriate Technology; Social Determinants of Health; Performance Expectancy; Diabetes; Asian Americans

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Equitable access to health information and improving health communications is part of the U.S. Department of Health and Human Services' *Healthy People 2030* Initiative with an overall goal to improve health and well-being.¹ The rising use of health information technology (e.g., digital health) facilitates effective communication, which is vital for health decision-making and patient-centered care. Digital health is a broad category that includes mobile health (mHealth), wearable devices, telehealth, and telemedicine.² Studies have demonstrated digital health is cost-effective and leads to positive health outcomes such as improved disease management and prevention, mental health, and physical activity levels.³⁻⁸

Although digital health has grown over the past decades, the global COVID-19 pandemic has highlighted digital health's significance. As a result of this increased awareness and importance, many believe that we will experience digital stickiness, the sustained use of technology to improve health and health care, post-pandemic.⁹ A consumer survey in the U.S. found that the use of digital health had over 10% penetration from January 2020 to January 2021, with as many as 80% intending to continue using these resources post-COVID-19.⁹ American's health data has largely been digitized with billions of federal investments in health information technology such as the HITECH, 21st Century Cures Act, myHealtheData, and the Blue Button 2.0.^{10,11} With the continued initiatives in ensuring equitable access to and sharing of health data using digital platforms, there is a need to understand different factors that may impact the use of digital health or exchange of health data.

The diffusion of digital health has led to significant growth of patient-generated health data (PGHD), consequently leading to the integration of PGHD into clinical patient-centered care.^{12,13} Several recent studies have examined people's information-sharing behaviors and found that many adults are willing to share wearable monitoring data with providers, family, or friends.^{14,15} While people may have general concerns about privacy and the context of using their personal information, they seem more willing to share their health-related information when they believe there is greater mechanism to protect their data in the system (e.g., EHR data).^{16,17} Yet, it is possible that there are personal and/or social characteristics or factors that may impact one's willingness to use digital health or share health information widely, for example, an individual's limited experience with technology, or lack of trust in health system. Aside from the tipping point brought by COVID-19 and the push of federal initiatives to use digital health, there is limited understanding of the personal and social factors that may predict digital health usage and information sharing behaviors for Americans.

In this study, we used a conceptual framework that is grounded in theories of technology adoption, to advance our understanding of digital health usage and information-sharing behaviors and explore associated potential factors. In addition to sociodemographic factors, we examined how health-related and technology-related factors (i.e., performance expectancy of digital health) were associated with information-sharing behaviors. Considering the potential challenges for universal acceptance of digital health (e.g., poor user experience, lack of interest, inequitable access to health information and digital resources), and the need to share health information using digital platforms, gaining insights

on these characteristics can provide opportunities for understanding disparities within and across different characteristics and inform future program design and policy changes,^{18,19}

Specific aims of this study were: 1) to describe the prevalence of digital health usage and information-sharing behaviors among American adults, 2) to examine factors that explain digital health usage by the following characteristics: health-related, technology-related, and sociodemographic factors; and 3) to explore the impact of these characteristics and digital health usage on adults' information-sharing behaviors with health care providers (HCP), family and friends, and social media, respectively.

Methods

Conceptual framework

We used a newly generated Digital Health Information Sharing and Usage (DHISU) conceptual framework to ground this study (See Supplemental Digital Content Figure SC1). This conceptual framework is based on the Unified Theory of Acceptance and Use of Technology (UTAUT)²⁰ and Chandrasekaran's conceptual model.²¹ In this framework, information sharing behaviors is posited by sociodemographic, health-related, and technology-related factors, as well as digital health usage. Similarly, digital health usage is associated with these factors and certain other characteristics such as performance expectancy (PE), device ownership, chronic conditions, age, education, rurality, and others.

Data source

The U.S. Health Information National Trends Survey (HINTS)[®] is an ongoing and nationally representative survey assessing the barriers to health information usage and identifying patterns, needs, and opportunities in health communication. The National Cancer Institute started conducting HINTS in 2003. Data for this study came from the HINTS 5, Cycle 4 ($N=3865$), collected from February 24, 2020, to June 15, 2020. This cycle was completely administered using a self-reported mail questionnaire; a web option was unavailable. The unweighted total household response rate for this cycle was 36.7%.²² Additional information on HINTS and its methodology can be found on the HINTS website, including the full sampling and weighting process.²² As we analyzed de-identified, publicly available data, we did not seek Institutional Review Board (IRB) approval.

Measurements

We used responses to several survey questions to operationalize the concepts in this study. See Table 1 for a succinct description of the concepts measured and how these concepts were measured using the HINTS survey items. We have also provided a more comprehensive description of these concepts in the Supplemental Digital Content Table SC2. For all the variables, we excluded responses that were "Missing data (Not Ascertained)," "Multiple responses selected in error," "question answered in error (commission in error)," and "Inapplicable" from the analyses.

Outcome measures—There were four primary outcomes for this analysis: 1) digital health usage, 2) information-sharing behaviors of adults with their healthcare providers

(HCP), 3) information-sharing behaviors with family or friends, and 4) information-sharing behaviors to social media.

Digital health usage.

This outcome measure is defined as the use of digital health, such as smartphones, tablets, or computers, to gather information, monitor health, or make clinical decisions in the past 12 months. Overall digital health usage referred to any digital experience of an individual, e.g., downloaded their online medical record, used a wearable device to track health, or used any digital health device to communicate to their provider, viewed medical results, or made health appointments. We identified digital health usage using responses to any of the five survey questions that allowed for a “yes” or “no” response; consequently, we treated these items as binary variables (see Table 1 or Supplemental Digital Content SC2).

Information-sharing behaviors.

Using Wang, Zhuang, Shao²³ description, we defined information-sharing in this study as an individual’s voluntary behavior or willingness to share or exchange health data information. We measured three different binary information-sharing behaviors outcomes (yes/no): information sharing with 1) an HCP, 2) family or friends, 3) social media.

Information sharing with an HCP was identified based on the survey response of a) “Have you shared health information from either an electronic monitoring device or smartphone with a health professional within the last 12 months?” b) “Would you be willing to share health data from your wearable device with your health care provider?”

Information sharing with family or friends was identified by two survey questions: a) “Would you be willing to share health data from your wearable device with your family?” (“yes” or “no”) or b) “Would you be willing to share health data from your wearable device with your friends?” (“yes” or “no”).

Information sharing to social media was identified by two survey questions: a) “In the last 12 months, have you used the internet to share health information on social networking sites, such as Facebook or Twitter?” (“yes” or “no”) or b) “In the last 12 months, have you used the internet to participate in an online forum or support group for people with a similar health or medical issue?” (“yes” or “no”).

Covariates—We included several covariates in the analysis as predictor variables. These measures included the respondents’ sociodemographic, health-related, and technology-related factors (see Table 1 or Supplemental Digital Content SC2).

Sociodemographic factors.

To measure sociodemographic, we included age (years), marital status (“married or currently living together” or “divorced, widowed, separated or single”), education (“less than high school or school other than college” or “some college to postgraduate”), race (“White”, “Black”, “American Indian or Alaskan Native”, “Asian American Pacific Islander”,

“Hispanic”, or “Multiple races”), gender (“Female” or “Male”), income ranges (“\$0K - \$35K”, “\$36K-\$100K”, or “>\$100K”), and rurality (“Metro areas” or “Non metro areas”).

Health-related factors.

These factors included history of chronic conditions and health insurance ownership. We used the survey items that asked if respondents had any history of chronic conditions (“yes” or “no”) including prior diagnosis of diabetes, high blood pressure, heart condition, lung disease, and depression. For health insurance, we used the survey item asking if respondents have insurance coverage (“yes” or “no”).

Technology-related factors.

These factors included digital health performance expectancy (PE; see operationalization below), digital device ownership (tablet, smartphone, basic cellular phone, multiple devices, or none), access to the internet, and if they ever been offered online access to their medical records (patient portal) by their HCP.

Specifically, the concept of PE was borrowed from the UTAUT,²⁰ and we defined it as the degree to which an individual perceives that using a digital health resource will help them track health goals, assist communication with their provider or help with treatment decision-making. We used three survey questions to operationalize this concept. These survey questions asked respondents if their digital health resource helped them track progress on a health-related goal (“yes” or “no”), helped make a treatment decision about an illness or condition (“yes” or “no”), and helped discuss health-related content with their healthcare provider (“yes” or “no”). A composite variable (a response of “yes” to any of the survey questions above) was then used as the measure for PE.

Data analysis

Weighted frequency analyses were performed to assess the pattern and distribution of digital health usage, information sharing behaviors, and demographic and health-related characteristics. A weighted unadjusted and adjusted multivariable logistic regression was conducted to determine the predictors associated with digital health usage and information sharing behaviors with HCP, families and friends, and social media, respectively. All analyses were conducted using Stata (version 16) to address the complex survey design of the HINTS 5 Cycle 4 sample by using weights and jackknife variance estimations provided by HINTS. The weighted percentages, unadjusted and adjusted odds ratio (OR), and 95% confidence intervals (CI) were calculated. The listwise deletion for each model was used to handle missing data, which was <10%. The level of significance was .05.

Results

Summary of sociodemographic characteristics

Table 2 shows the weighted sociodemographic characteristics. Most adults were males, white, married, and had obtained at least a high school degree. The mean age was 46.8 years old ($SE = .30$). Almost three-quarters had a median income of more than \$35,000, which is middle-income.²⁴ Many lived in a metropolitan area with the coverage of health insurance.

Prevalence of digital health usage and information-sharing behaviors

The prevalence of digital health usage and information sharing behaviors among American adults are reported in Table 3 (with 95% CI). About 72% of adults reported using a digital health in the past 12 month, with almost 50% using an electronic device to make healthcare appointments, followed by 47.1% using digital platforms to talk to a doctor and 42.2% to check test results. Many were also willing to share health data from their wearable device with their HCP (81.3%) or family members (74.9%), while only 57.7% were willing to share it with their friends. Only 14.2% of American adults were willing to share health information on social media/social networking sites online forums and a much lower percentage (9.8%) were willing to share information to support groups for people with similar health issues.

Multivariable logistic results

Figures 1–4 are forest plot diagrams of the adjusted odds ratio showing the different predictors or predictors to the outcome measures. Unadjusted and adjusted results with their corresponding p-values and 95% confidence intervals (CI) are in Supplemental Digital Content 2 Tables S3.1, S3.2, S3.3 and S3.4.

Predictors of digital health usage—In the adjusted multivariable analysis, male individuals (adjusted odds ratio [aOR]= 0.67, 95%CI, 0.44–1.00, $P = .05$), living in non-metro areas (aOR = 0.58, 95%CI, 0.34–1.00, $P = .05$), tablet users (aOR = 0.42, 95%CI, 0.21–0.84, $P = .02$) or having no digital device (OR = 0.28, 95%CI, 0.11–0.71, $P < .001$) had significantly lower odds of digital health usage holding all other variables constant (see Figure 1).

Individuals with some college education (aOR = 1.80, 95%CI, 1.25–2.58, $P < .001$), those who were offered patient portal access (aOR = 2.44, 95%CI 1.60–3.71, $P < .001$), and those who experienced positive PE (aOR = 4.17, 95%CI, 2.71–6.40, $P < .001$) had significantly higher odds of digital health usage holding all else constant (see Figure 1).

Predictors of information sharing behavior with healthcare providers (HCP)—In examining the determinants to information sharing behaviors with their HCP (see Figure 2), Asian American Pacific Islanders (AAPI; aOR = 0.52, 95%CI, 0.28–0.96, $P = .04$), those who have diabetes (aOR = 0.65, 95%CI, 0.43–0.99, $P = .05$) and owning a tablet computer (over those who are smartphone owners; aOR = 0.32, 95%CI, 0.12–0.82, $P = .02$) had significantly lower odds of sharing information to their HCP holding all other variables constant.

Individuals who had positive PE experience with digital health (aOR = 3.78, 95%CI, 2.41–5.92, $P < .01$) and digital health usage (aOR = 14.3, 95%CI, 6.17–32.98, $P < .001$) had significantly higher odds of sharing their information to their HCP holding all else constant (see Figure 2).

Predictors of information sharing behavior with family or friends—Individuals who own a tablet (aOR = 0.26, 95%CI, 0.07–0.92, $P = .04$) or have a basic cell phone only

(aOR = 0.65, 95%CI, 0.44–1.00, $P = .05$) had significantly lower odds of sharing their health information with family and friends (see Figure 3).

Individuals who identified with multiple races (aOR = 1.76, 95%CI, 1.02–3.05, $P = .04$) or had a positive PE experience (aOR = 3.28, 95%CI, 1.84–5.95, $P < 0.001$) had significantly higher odds of sharing health information with family and friends, holding all else constant (see Figure 3).

Predictors of information sharing behavior in social media—Holding all other variables constant, we found that being male (aOR = 0.56, 95%CI 0.39–0.79, $P < .001$) and having an annual income between \$36K–\$100K (aOR = 0.57, 95%CI, 0.38–0.86, $P = .008$) had significantly lower odds of sharing health information in social media (see Figure 4).

Those who had depression (aOR = 1.46, 95%CI 1.00–2.12, $P = .05$), has had a positive PE experience (aOR = 1.72, 95%CI 1.10–2.69, $P = .02$), or those who have used a digital health resource (aOR = 3.11, 95%CI 1.58–6.09, $P < .001$) had significantly higher odds of sharing health information in social media, holding all else constant (see Figure 4).

Discussion

The overall goal of this study was to understand the prevalence and predictors of digital health usage and information-sharing behaviors among American adults. Our findings indicated an overall high rate of digital health usage; most American adults were willing to share their wearable device data with their HCP, and family or friends. The results also suggested that gender, education, living in a metro/non-metro area, types of device ownership, patient portal access, and digital health performance expectancy (PE) were independent factors associated with digital health usage. Similarly, gender, education, income, chronic diseases (such as diabetes, hypertension, lung disease, and depression), types of device ownership, patient portal access, PE of digital health, and digital health usage were associated with information-sharing behaviors.

Digital health usage

Overall, we saw substantial use of digital health, particularly the use of electronic devices to make appointments, check test results, and communicate with their HCP. Many of these practices are often facilitated by the patient portal, enabling patient-provider engagement.²⁵ Although a previous study indicated that about 60% of adults do not use a portal,²⁶ this national survey analysis suggests that individuals are willing to use digital health to get instant access to test results, book appointments, and communicate with providers.

This study indicates a segment of American adult population – men, those in non-metro areas, those that used a tablet or did not have a digital device- disproportionately under-utilized digital health. The phenomenon of digital inequity is not new; prior studies have shown structural barriers to digital connectivity.^{27,28} This study corroborates the lack of access to digital devices remain as a barrier to digital health usage, suggesting digital access is also a social determinant of health.²⁹ Although mobile device ownership has drastically improved over the years, with over 85% of Americans now owning a smartphone device,³⁰

digital health inequity persists among those who own devices versus those who do not, which can potentially influence achieving the patient-centered care goals promoted by the Office of the National Coordinator for Health Information Technology.³¹ There is a need to think of systematic approaches to expand access to digital health resources and services, further engage individuals who own devices, and prioritize and reach out to non-digital device users to close the digital health inequity.³²

The persistent digital divide between rural and urban areas was also highlighted in this study and consistent with reports in the literature.^{33,34} The lack of or limited access to internet broadband services can be one of the major reasons for the unequal digital health usage in rural areas.³⁴ Indeed, Americans living in rural areas had lower levels of technology ownership and broadband adoption compared to Americans in urban areas.³⁵ Creative approaches to increasing digital connectivity have been proposed such as the use of local to federal services to distribute mobile devices or data plans.²⁷

The type of devices owned by an individual appears to matter in digital health usage, as this study found that tablet users were less likely to use digital health compared to smartphone users. With the increasing usage of different types of mobile health technologies, it is important to understand that not all devices are created equal. A study on older adults' perceptions of technology reported the barriers to using tablets, including lack of instructions, low self-efficacy, cost, health-related challenges, too complex technology, and negative features.³⁶ Therefore, it is essential to design user friendly interfaces to meet various individuals' needs.³⁷ Understanding the facilitators and barriers to use of phone or tablet technologies is vital to maximizing the potential of these platforms to facilitate improving health and well-being.

Information sharing behaviors

We found that the most significant predictors to information sharing behaviors (with HCP, social media sites, or with family or friends) were digital health usage and performance expectancy (PE). It is understandable that people who value the benefits of using digital health are more likely to share their data and information. Prior studies have demonstrated that PE is determinant of intention to use digital health technology.^{38,39} Similarly, this study found that PE was also a significant determinant of digital health information sharing. This has implications in developing digital health resources to meet users' expectations. Researchers and developers need to make sure that digital health resources are designed to assist individuals in tracking their health progress and providing them with clinical decision support capabilities.

Digital information sharing behaviors can be potentially associated with health disparity. In this study we found that Asian American Pacific Islanders (AAPI), compared to non-Hispanic whites, were less likely to share information with their HCP. This may be due to the different complex barriers experienced by AAPIs, including cultural, language, and systemic challenges, discrimination, and racism.^{40,41} This also serves as an opportunity to disaggregate AAPI data further to identify the different variations across AAPI subgroups.⁴² AAPIs are viewed as a model minority, a myth rooted in Anti-Blackness, which masks many

of AAPIs' health needs, including the challenges faced with sharing health information with HCPs.

Although there is an increased interest in using digital technologies such as telehealth among individuals with diabetes with high satisfaction rates and improved autonomy,⁴³ we found in this study that those diagnosed with diabetes were 34% less likely to share information with their HCP. This is in contrast with prior studies establishing that individuals with chronic conditions are more likely to share health information due to their increased health system interaction.⁴⁴ With the increasing availability of patient-generated health data, sharing health information with care providers is valuable to improve communication and facilitate patient care.⁴⁴ In a 2014 cross-sectional study of health information sharing behaviors of 1800 households in the US, they showed that trust in confidentiality and competency of providers were associated with patients' behaviors and expectations to share information in healthcare.⁴⁵ This suggests the need to investigate further why individuals with diabetes are hesitant to share information with their HCP. This has considerable implications in terms of self-and disease management of diabetes, particularly when leveraging digital health to self-management.

Implications to Nursing Practice

From a praxis perspective, the findings of this study are valuable for staff nurses and nurse informaticists in addition to researchers. Digital health technology is helping to revolutionize healthcare. It is important to reframe nurse-patient relationships in the digital age, as Booth and colleagues have noted.⁴⁶ Nurses need to understand how to make the most of this digital environment and adopt to the changing healthcare landscape. Given that nearly two-thirds of American adults are using digital health, its impact on nursing and nursing practice is inevitable. Nurses should take action to be at the forefront of digital health or risk missing the opportunity to take part in the creation of new roles, knowledge production, and policy and community engagement on digital health technologies.⁴⁶

As patient advocates, nurses must strive for digital health equity and be proactive in bridging the digital divide. This study has shown that certain segments of the population - often marginalized groups - such as those living in rural areas and non-owners of digital devices are barriers to digital health use and information-sharing. Nurses can conduct personalized assessment, work together with nurse informaticists to develop effective digital health programs, and support communities to have the digital health capacity needed to fully engage in the changing healthcare landscape.

For instance, offering patient portal access at the time of admission or discharge is an important step in making sure patients are aware of this supportive digital health resource. For nurse informaticists, participating in the design, implementation, or evaluation of digital health resources will provide nurses with a seat at the table, paying close attention to important predictors on digital health use and information sharing reported in this study such as performance expectancy. For nurse leaders and educators, building leadership in digital health and creating training opportunities in informatics (such as digital health, human-centered design, implementation science, and digital science) are critically needed.^{46,47}

This study also helps us understand information sharing behaviors for health and provides some guidance to nurses. As mentioned earlier, when users' perception of the relevancy of digital health to their healthcare needs (i.e., positive performance expectancy) are met, they are more likely to use digital health and share health information. Consequently, there needs to be a collaborative effort among researchers, developers, and clinicians to ensure that digital health resources are patient- or user-centric with consideration to the complexity of managing health.

Limitations

Because this was a cross-sectional study, we did not examine causal relationships between predictor and outcome variables. The survey is also self-reported, which can be subjective and interpreted differently by respondents. This cycle of the HINTS was only available as a mail-in questionnaire with no web option. This may have biased the sample to those willing to mail in the survey; we would then expect that our estimates would be possible under-estimates of digital health usage since those who would prefer an online, web option might be more apt to use digital health. Some of the calculated confidence intervals also had a wide range (e.g., American Alaskan or Native American and information sharing with HCP) due to small sample sizes. This supports our discussion on disaggregating data and the need to oversample marginalized populations. Nonetheless, any conclusions drawn from the data with wide CI may need to be replicated with a larger sample size. Finally, although we controlled for various covariates, including age, gender, income, race, education (i.e., variables that are typically treated as covariates in other prior HINTS-based studies), unmeasured confounding is a possible limitation in all cross-sectional analyses.

Conclusion

With the tipping point of shifting to digital health brought on by COVID-19, there is great potential to push for widespread adoption of digital health and information-sharing. With many benefits to utilizing digital resources and sharing digital health information, we need to effectively capitalize on this opportunity to realize the different initiatives of the U.S. government related to information sharing. By thinking of different ways to engage individuals and communities who are less likely to use resources and share health information, we can close the disparity and digital inequity in the U.S. There is a need to advocate for making digital health be more usable and have the capabilities to self-track and monitor health and assist in clinical decision to enable the usage and improve information-sharing behaviors.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Data Availability Statement:

The data that support the findings of this study are openly available in National Cancer Institute Health Information National Trends Survey® at <https://hints.cancer.gov/data/download-data.aspx>.

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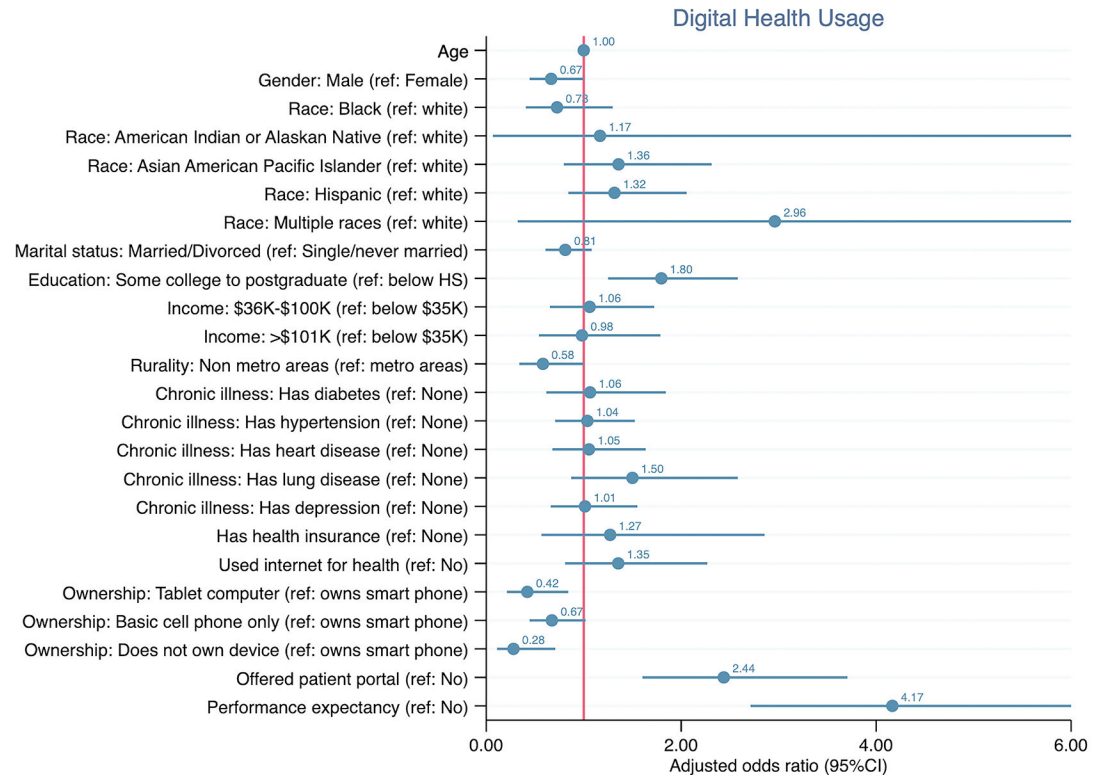


Figure 1:

Multivariable logistic regression forest plot results showing the predictors of digital health usage.

Note: Authors' analysis of data from the HINTS® 5 Cycle 4. We present the results using aOR (95%CI). Some wide 95% CIs are truncated. The left-hand column of the forest plot lists the different covariates included in the study with the reference (ref) variable. The right-hand column is a plot of the odds ratio for each of the variables represented by a circle incorporating confidence intervals represented by horizontal lines. The vertical line represents no effect (aOR = 1). Confidence intervals for each variable overlapping with this vertical line demonstrates that at 95%CI, their odds ratio do not differ from the reference variable. Please refer to supplemental content for detailed results (including p-values).



Figure 2:

Multivariable logistic regression forest plot results showing the predictors of digital information sharing behaviors with healthcare providers.

Note: Authors' analysis of data from the HINTS® 5 Cycle 4. We present the results using aOR (95%CI). Some wide 95% CIs are truncated. The left-hand column of the forest plot lists the different covariates included in the study with the reference (ref) variable. The right-hand column is a plot of the odds ratio for each of the variables represented by a square incorporating confidence intervals represented by horizontal lines. The vertical line represents no effect (aOR = 1). Confidence intervals for each variable overlapping with this vertical line demonstrates that at 95%CI, their odds ratio do not differ from the reference variable. Please refer to supplemental content for detailed results (including p-values).

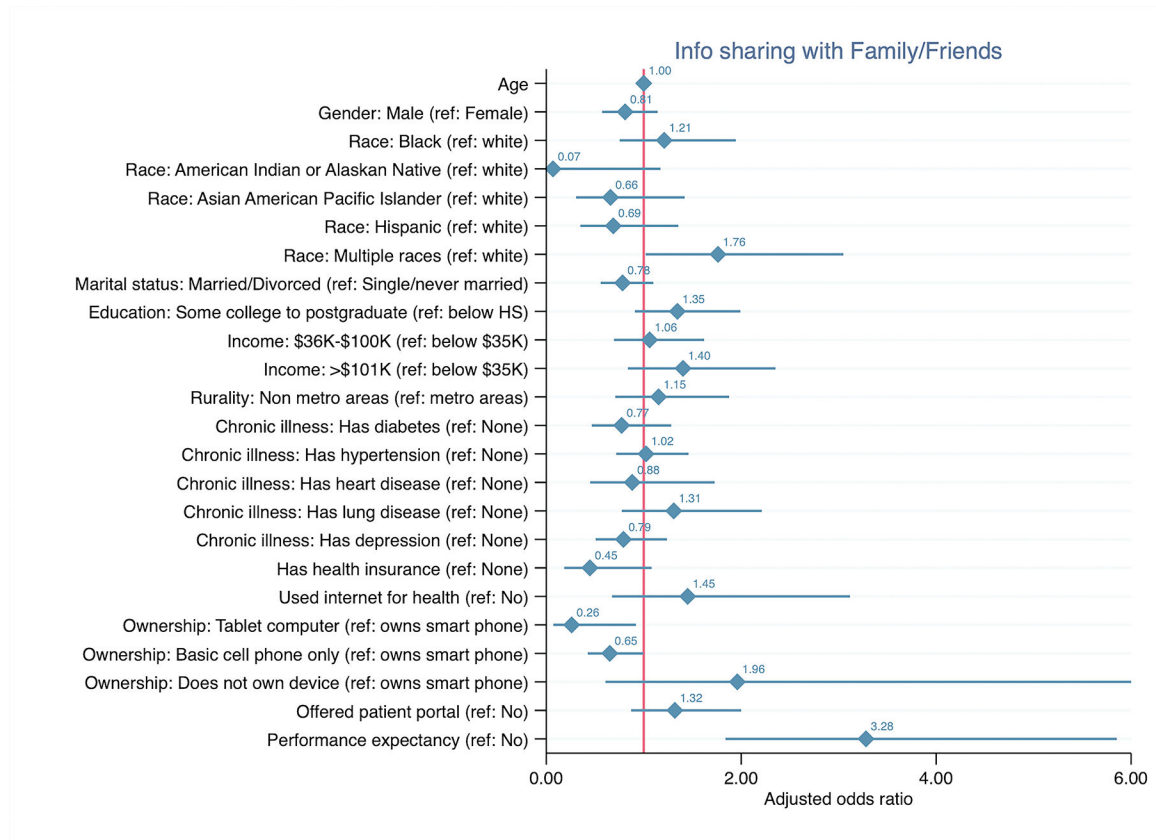


Figure 3:

Multivariable logistic regression forest plot results showing the predictors of digital information sharing behaviors with family or friends.

Note: Authors' analysis of data from the HINTS® 5 Cycle 4. We present the results using aOR (95%CI). Some wide 95% CIs are truncated. The left-hand column of the forest plot lists the different covariates included in the study with the reference (ref) variable. The right-hand column is a plot of the odds ratio for each of the variables represented by a diamond incorporating confidence intervals represented by horizontal lines. The vertical line represents no effect (aOR = 1). Confidence intervals for each variable overlapping with this vertical line demonstrates that at 95%CI, their odds ratio do not differ from the reference variable. Please refer to supplemental content for detailed results (including p-values).

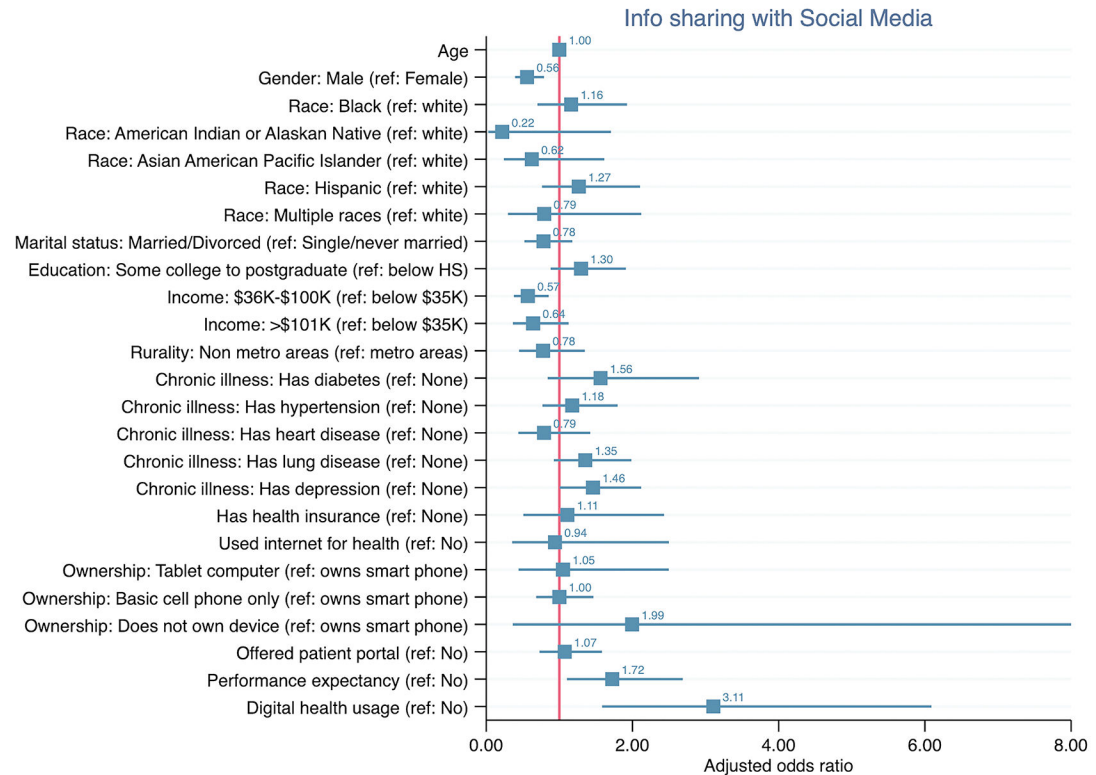


Figure 4:

Multivariable logistic regression forest plot results showing the predictors of digital information sharing behaviors with social media.

Note: Authors' analysis of data from the HINTS® 5 Cycle 4. We present the results using aOR (95% CI). Some wide 95% CIs are truncated. The left-hand column of the forest plot lists the different covariates included in the study with the reference (ref) variable. The right-hand column is a plot of the odds ratio for each of the variables represented by a square incorporating confidence intervals represented by horizontal lines. The vertical line represents no effect (aOR = 1). Confidence intervals for each variable overlapping with this vertical line demonstrates that at 95% CI, their odds ratio do not differ from the reference variable. Please refer to supplemental content for detailed results (including p-values).

Table 1.

Operationalization of outcome and predictor variables

Concept Measured	Survey Items Description	Level of Measurement
Outcome Variables		
Digital health usage	Composite of five survey items asking participants about the use of online medical record to download health information to digital device, use of wearable device to track health,, use of digital health to communicate with a doctor, the use of a digital health to look up medical test, and the use of digital health to make appointments.	Dichotomous
Information sharing behaviors with HCP	Composite of two survey items related to participants willingness to share health information from digital devices (either an electronic monitoring device, smartphone, or a wearable device) to a health professional.	Dichotomous
Information sharing to social media	Composite of two survey items pertaining to participants' behavior of sharing health information on social networking, online forum, or support group for people with similar health or medical issue.	Dichotomous
Information sharing with family or friends	Composite of two survey items asking participants about their wiliness to share health data from wearable device with family or friends.	Dichotomous
Predictor variables		
Sociodemographic factors	Seven survey items related to age, education, race, gender, income, rurality	Categorical and Continuous
Health related factors	Six survey items about participants' chronic conditions (such as diabetes) and health insurance coverage	Dichotomous
Technology related factors	Three survey items related to participants' technology-related characteristics such as the use of the internet, type of device digital device owned, and history of being offered patient portal (online access).	Categorical
Digital health performance expectancy	Composite of three survey items related to an individual's experience or perception of the usefulness of digital health	Dichotomous

Table 2.Sample characteristics. $N = 3,865$

	% (weighted)
Age	
Sex	
Male	50.1
Female	49.0
Race	
White	63.3
Black	11.1
American Indian/Native American	0.1
Asian American	5.7
Hispanics/Latinos	17.0
Multiple races	2.3
Marital status	
Married or living with someone currently	54.8
Divorced, separated or single	45.2
Education	
Less than high school or technical	39.2
Some college to postgraduate	60.8
Income	
\$0 to \$35,000	26.6
\$36K-\$100,000	43.3
>\$101K	30.1
Metro/Non-metro	
Metro	87.8
Non-metro area	12.2
Chronic conditions	
Have diabetes	18.0
Have high blood pressure	36.1
Have heart condition	8.1
Have lung disease	12.7
Have depression	24.3
Health insurance	
Yes	91.0
No	9.0

Table 3.

Weighted frequency of digital usage and information sharing behaviors

Outcome variables	% Weighted (95%CI)
Digital Health Usage (un the past 12 months)	
Download records online	31.5 (27.5,35.6)
Use of wearable devices to track health	30.2 (27.8,32.6)
Use electronic device to talk to doctor	47.1 (44.8,49.5)
Use electronic device to check test results	42.2 (39.3,45.3)
Use electronic device to make appointments	49.4 (46.6,52.1)
Overall digital health usage	71.2 (69.0,73.6)
Information sharing behaviors - PCP	
Shared health information from either an electronic monitoring device or smartphone with a health professional within the last 12 months	14.2 (12.7,15.9)
Would you be willing to share health data from your wearable device with your health care provider?	81.3 (75.9,85.7)
Information sharing behaviors – family or friends	
Would you be willing to share health data from your wearable device with your family?	74.9 (69.4,79.7)
Would you be willing to share health data from your wearable device with your friends?	57.7 (52.1,63.1)
Information sharing behaviors – social media	
In the last 12 months, have you used the internet to share health information on social networking sites, such as Facebook or Twitter?	14.2 (12.5,16.1)
In the last 12 months, have you used the internet to participate in an online forum or support group for people with a similar health or medical issue?	9.8 (8.4,11.4)