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Determinants of American Adults' Use of Digital Health and Willingness to Share Health Data to Providers, Family, and Social Media

A Cross-sectional Study

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With the global pandemic driving the adoption of digital health, understanding the 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 (eg, 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 with 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.

KEY WORDS: Asian Americans, Culturally appropriate technology, Diabetes, Digital divide, Information sharing, Mobile health, Performance expectancy, Social determinants of health

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The authors have disclosed that they have no significant relationships with, or financial interest in, any commercial companies pertaining to this article.

Dr Tolentino was supported by the National Clinician Scholars Program at the Institute for Healthcare Policy and Innovation and the School of Nursing at the University of Michigan, Ann Arbor, at the time of this study. This project is supported by the Agency for Healthcare Research and Quality under grant R01HS027846. The content is solely the responsibility of the authors and does not necessarily represent the official views of the Agency for Healthcare Research and Quality.

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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Supplemental digital content is available for this article. Direct URL citations appear in the printed text and are provided in the HTML and PDF versions of this article on the journal's Web site (www.cinjournal.com).

DOI: 10.1097/CIN.0000000000001025

Equitable access to health information and improving health communications is part of the US 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 (eg, 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, wearable devices, telehealth, and telemedicine.[2] Studies have demonstrated that 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 healthcare, postpandemic.[9] A consumer survey in the United States 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] Americans' health data have 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 the 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, consequently leading to the integration of patient-generated health data 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] Although 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 (eg, 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 (ie, performance expectancy [PE] of digital health) were associated with information-sharing behaviors. Considering the potential challenges for universal acceptance of digital health (eg, 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 the 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 healthcare providers (HCPs), family and friends, and social media, respectively.

METHODS

Conceptual framework

We used a newly generated Digital Health Information Sharing and Usage conceptual framework to ground this study (See Supplemental Digital Content Figure SC1, http://links.lww.com/CIN/A255). This conceptual framework is based on the Unified Theory of Acceptance and Use of Technology[20] and Chandrasekaran's[21] conceptual model. In this framework, information-sharing behaviors are 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 PE, device ownership, chronic conditions, age, education, rurality, and others.

Data Source

The US 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 deidentified, publicly available data, we did not seek institutional review board 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, http://links.lww.com/CIN/A256. 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 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, for example, 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

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 PE	Composite of three survey items related to an individual's experience or perception of the usefulness of digital health	Dichotomous

a "yes" or "no" response; consequently, we treated these items as binary variables (see Table 1 or Supplemental Digital Content SC2, http://links.lww.com/CIN/A256).

Information-Sharing Behaviors

Using Wang et al's[23] 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 (1) "Have you shared health information from either an electronic monitoring device or smartphone with a health professional within the last 12 months?" and (2) "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: (1) "Would you be willing to share health data from your wearable device with your family?" ("yes" or "no") and (2) "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: (1) "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 (2) "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, http://links.lww.com/CIN/A256).

Sociodemographic Factors

To measure sociodemographic factors, 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" [AAPIs], "Hispanic," or "Multiple races"), gender ("Female" or "Male"), income ranges ("$0 K-$35 K," "$36 K-$100 K," or ">$100 K"), and rurality ("Metro areas" or "Nonmetro 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 previous 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 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 Unified Theory of Acceptance and Use of Technology,[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 HCP ("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 HCPs, 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 (aOR), and 95% confidence intervals (CIs) 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 men, White, and married and had obtained at least a high school degree. The mean age was 46.8 years (SE, 0.30). 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.

Table 2. Sample Characteristics (N = 3865)

	% (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-$35 000	26.6
$36 000-$100 000	43.3
>$101 000	30.1
Metro/Nonmetro	
Metro	87.8
Nonmetro 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

Prevalence of Digital Health Usage and Information-Sharing Behaviors

The prevalence of digital health usage and the information-sharing behaviors among American adults are reported in Table 3 (with 95% CI). About 72% of adults reported using 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%), whereas 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 and online forums, and a much lower percentage (9.8%) were willing to share information to support groups for people with similar health issues.

Table 3. Weighted Frequency of Digital Usage and Information-Sharing Behaviors

Outcome Variables	% Weighted (95% CI)
Digital health usage (in 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—HCP	
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)

Multivariable Logistic Results

Figures 1 to 4 are forest plot diagrams of the aORs showing the different predictors or predictors to the outcome measures. Unadjusted and adjusted results with their corresponding *P* values and 95% CI are in Supplemental Digital Content 3 Tables S3.1, S3.2, S3.3 and S3.4, http://links.lww.com/CIN/A257.

Predictors of Digital Health Usage

In the adjusted multivariable analysis, male individuals (aOR, 0.67; 95% CI, 0.44-1.00; $P = .05$), those living in nonmetro 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 those having no digital device (odds ratio, 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

In examining the determinants to information-sharing behaviors with their HCP (see Figure 2), AAPIs (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 those 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; $P < .001$) 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 men (aOR, 0.56; 95% CI, 0.39-0.79; $P < .001$) and those having an annual income between \$36 000 and \$100 000 (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; $P = .05$), have had a positive PE experience (aOR, 1.72; 95% CI, 1.10-2.69; $P = .02$), or 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 indicate 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 suggest that

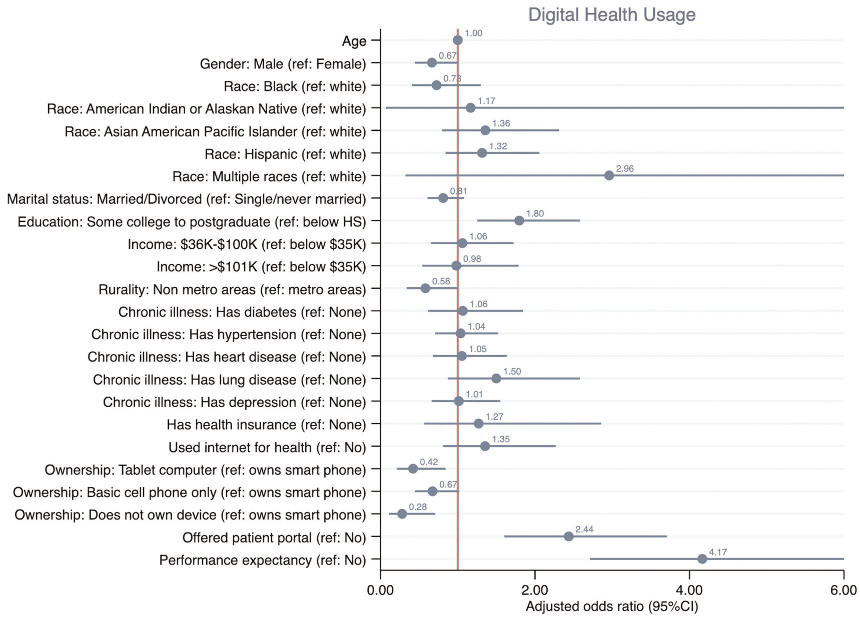

FIGURE 1. Multivariable logistic regression forest plot results showing the predictors of digital health usage. Note: Authors' analysis of data from the HINTS 5 Cycle 4. We present the results using aOR (95% CI). Some wide 95% CIs are truncated. The left-hand column of the forest plot lists the different 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 CIs represented by horizontal lines. The vertical line represents no effect (aOR, 1). Confidence intervals for each variable overlapping with this vertical line demonstrate 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).

gender, education, living in a metro/nonmetro area, types of device ownership, patient portal access, and digital health 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 that a segment of the American adult population—men, those in nonmetro areas, those who used a tablet, or those who did not have a digital device—disproportionately underutilized digital health. The phenomenon of digital inequity is not new; previous studies have shown structural barriers to digital connectivity.[27,28] This study corroborates that the lack of access to digital devices remains as a barrier to digital health usage, suggesting that 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 nondigital 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 with 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]

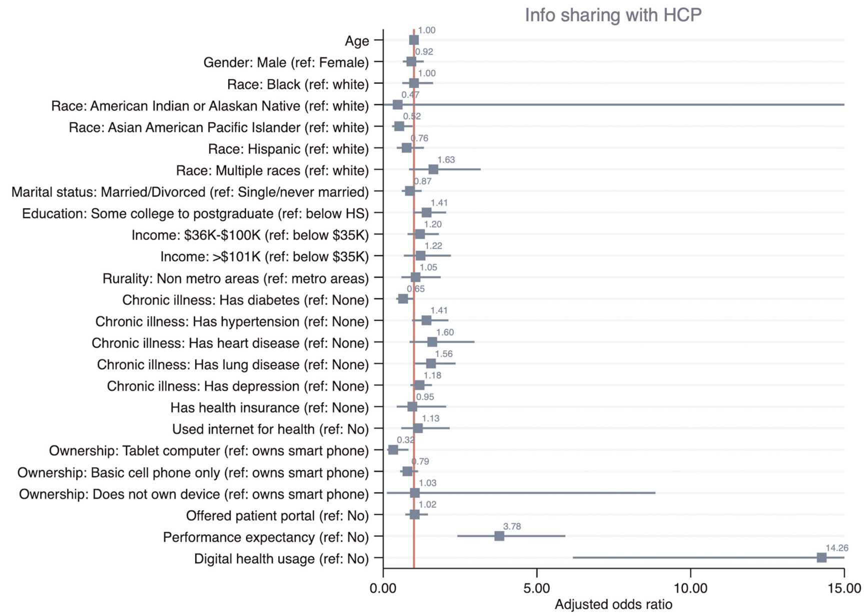

FIGURE 2. Multivariable logistic regression forest plot results showing the predictors of digital information-sharing behaviors with HCPs. Note: Authors' analysis of data from the HINTS 5 Cycle 4. We present the results using aOR (95% CI). Some wide 95% CIs are truncated. The left-hand column of the 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 CIs represented by horizontal lines. The vertical line represents no effect (aOR, 1). Confidence intervals for each variable overlapping with this vertical line demonstrate 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).

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 with 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 PE. It is understandable that people who value the benefits of using digital health are more likely to share their data and information. Previous studies have demonstrated that PE is a 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 AAPIs, compared with 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] Asian American Pacific Islanders 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 previous studies establishing that individuals with chronic conditions are more likely to share health information due to their increased health system

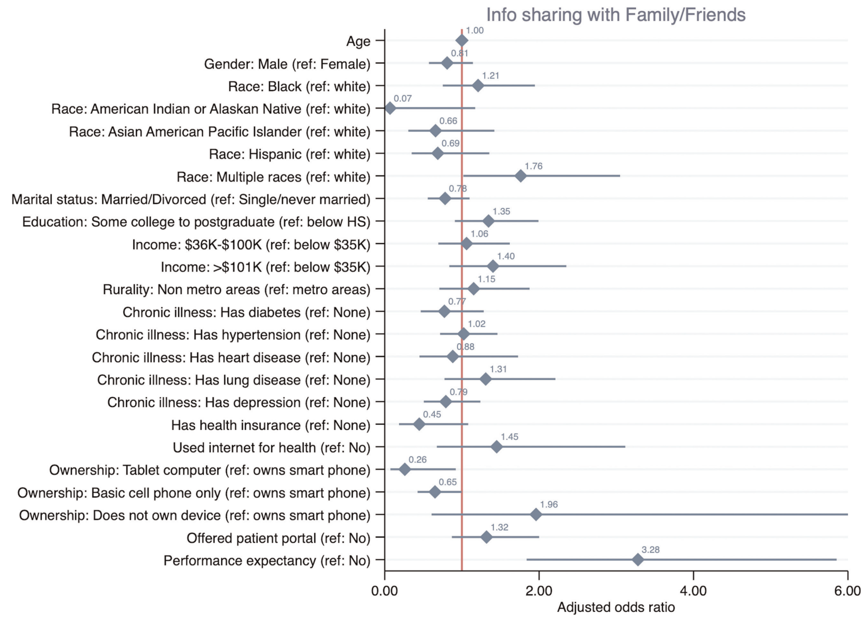

FIGURE 3. Multivariable logistic regression forest plot results showing the predictors of digital information-sharing behaviors with family or friends. Note: Authors' analysis of data from the HINTS 5 Cycle 4. We present the results using aOR (95% CI). Some wide 95% CIs are truncated. The left-hand column 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 CIs represented by horizontal lines. The vertical line represents no effect (aOR, 1). Confidence intervals for each variable overlapping with this vertical line demonstrate 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).

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 United States, it was shown 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[46] have noted. Nurses need to understand how to make the most of this digital environment and adapt 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 nonowners 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 engage fully 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 PE. For nurse leaders and educators, building leadership in digital health and

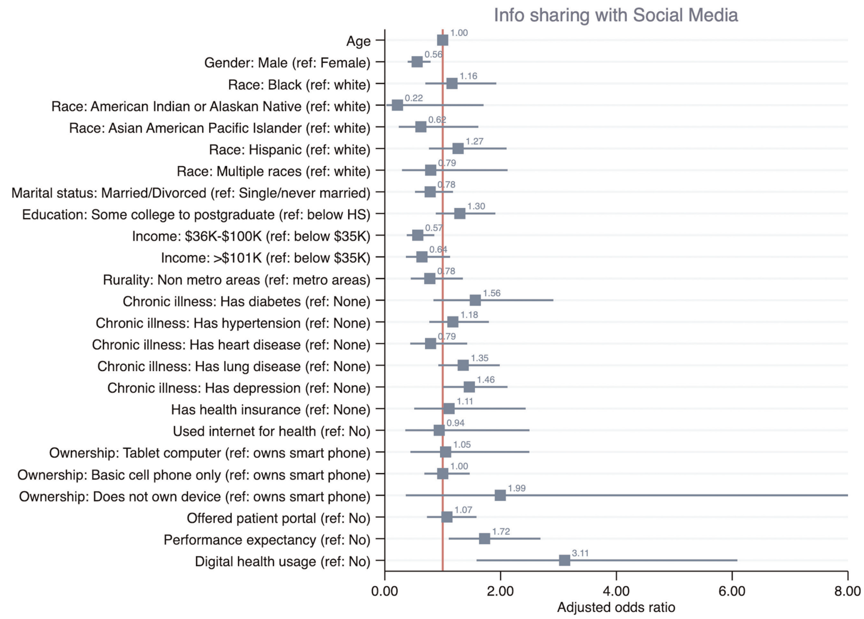

FIGURE 4. Multivariable logistic regression forest plot results showing the predictors of digital information-sharing behaviors with social media. Note: Authors' analysis of data from the HINTS 5 Cycle 4. We present the results using aOR (95% CI). Some wide 95% CIs are truncated. The left-hand column 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 CIs represented by horizontal lines. The vertical line represents no effect (aOR, 1). Confidence intervals for each variable overlapping with this vertical line demonstrate 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).

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 (ie, positive PE) 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 available only 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 underestimates 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 CIs also had a wide range (eg, 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 (ie, variables that are typically treated as covariates in other previous 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 capitalize effectively on this opportunity to realize the different initiatives of the US 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 United States. There is a need to advocate for making digital health 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.

References

1. US Department of Health and Human Services Office of Disease Prevention and Health Promotion. Healthy People 2030. 2021. https://health.gov/healthypeople
2. US Food and Drug Administration. What is digital health? Digital Health Center of Excellence website. 2020. https://www.fda.gov/medical-devices/digital-health-center-excellence/what-digital-health
3. Ching J, Kapoor K. Benefits, barriers, and impact of patient portals and mHealth applications. *Pharmacy Today*. 2017;23(10).
4. Baldwin JL, Singh H, Sittig DF, Giardina TD. Patient portals and health apps: pitfalls, promises, and what one might learn from the other. *Healthcare*. 2017;5(3): 81–85.
5. Vehi J, Regincos Isern J, Parcerisas A, Calm R, Contreras I. Impact of use frequency of a mobile diabetes management app on blood glucose control: evaluation study. *JMIR mHealth and uHealth*. 2019;7(3): e11933.
6. Li WW, Zhong J. A review of technology-based interventions in improving type 2 diabetes management in Chinese Americans. *Asian/Pacific Island Nursing Journal*. 2019;4(1): 20–33.
7. Howarth A, Quesada J, Silva J, Judycki S, Mills PR. The impact of digital health interventions on health-related outcomes in the workplace: a systematic review. *Digital Health*. 2018;4: 2055207618770861.
8. Jiang X, Ming WK, You JH. The cost-effectiveness of digital health interventions on the management of cardiovascular diseases: systematic review. *Journal of Medical Internet Research*. 2019;21(6): e13166.
9. McKinsey & Company. Survey: US consumer sentiment during the coronavirus crisis. 2021. https://www.mckinsey.com/business-functions/marketing-and-sales/our-insights/survey-us-consumer-sentiment-during-the-coronavirus-crisis
10. Office of the National Coordinator for Health Information Technology. 21st Century Cures Act: Interoperability, information blocking, and the ONC health IT certification program. US Government. https://www.healthit.gov/curesrule/
11. Centers for Medicare and Medicaid Services. CMS advances interoperability & patient access to health data through new proposals. 2019. https://www.cms.gov/newsroom/fact-sheets/cms-advances-interoperability-patient-access-health-data-through-new-proposals
12. Demiris G, Iribarren SJ, Sward K, Lee S, Yang R. Patient generated health data use in clinical practice: a systematic review. *Nursing Outlook*. 2019;67(4): 311–330.
13. Austin E, Lee JR, Amtmann D, et al. Use of patient-generated health data across healthcare settings: implications for health systems. *JAMIA Open*. 2020;3(1): 70–76.
14. Ratcliff CL, Krakow M, Greenberg-Worisek A, Hesse BW. Digital health engagement in the US population: insights from the 2018 Health Information National Trends Survey. *American Journal of Public Health*. 2021;111(7): 1348–1351.
15. Rising CJ, Gaysynsky A, Blake KD, Jensen RE, Oh A. Willingness to share data from wearable health and activity trackers: analysis of the 2019 Health Information National Trends Survey data. *JMIR mHealth and uHealth*. 2021;9(12): e29190.
16. Grande D, Mitra N, Iyengar R, et al. Consumer willingness to share personal digital information for health-related uses. *JAMA Network Open*. 2022;5(1): e2144787.
17. Seltzer E, Goldshear J, Guntuku SC, et al. Patients' willingness to share digital health and non-health data for research: a cross-sectional study. *BMC Medical Informatics and Decision Making*. 2019;19(1): 157.
18. US Department of Health and Human Services Office of Disease Prevention and Health Promotion. Health Communication. Healthy People 2030. HealthyPeople.gov. Healthy People 2020 website. https://health.gov/healthypeople/objectives-and-data/browse-objectives/health-communication
19. Whitelaw S, Pellegrini DM, Mamas MA, Cowie M, Van Spall HGC. Barriers and facilitators of the uptake of digital health technology in cardiovascular care: a systematic scoping review. *European Heart Journal. Digital Health*. 2021;2(1): 62–74.
20. Venkatesh V, Morris MG, Davis GB, Davis FD. Unified Theory of Acceptance and Use of Technology (UTAUT). *Management of Information Systems Quarterly*. 2003;27: 425–478.
21. Chandrasekaran R, Katthula V, Moustakas E. Patterns of use and key predictors for the use of wearable health care devices by US adults: insights from a national survey. *Journal of Medical Internet Research*. 2020;22(10): e22443.
22. National Cancer Institute. Health Informational National Trends Survey Public Use Dataset. 2020. https://hints.cancer.gov/data/download-data.aspx
23. Wang W, Zhuang X, Shao P. Exploring health information sharing behavior of Chinese elderly adults on WeChat. *Healthcare*. 2020;8(3): 207.
24. American Enterprise Institute. Three charts based on today's census report show that the US middle-class is shrinking…because they're moving up. 2019. https://www.aei.org/carpe-diem/three-charts-based-on-todays-census-report-show-that-the-us-middle-class-is-shrinking-because-theyre-moving-up/
25. Dendere R, Slade C, Burton-Jones A, Sullivan C, Staib A, Janda M. Patient portals facilitating engagement with inpatient electronic medical records: a systematic review. *Journal of Medical Internet Research*. 2019;21(4): e12779.
26. Anthony DL, Campos-Castillo C, Lim PS. Who isn't using patient portals and why? Evidence and implications from a national sample of US adults. *Health Affairs*. 2018;37(12): 1948–1954.
27. Salhi RA, Abir M, Salhi BA. No patient left behind: considering equitable distribution of telehealth. Health Affairs Blog. April 21, 2021. https://www.healthaffairs.org/do/10.1377/forefront.20210414.845933/full/
28. Cantor JH, McBain RK, Pera MF, Bravata DM, Whaley CM. Who is (and is not) receiving telemedicine care during the COVID-19 pandemic. *American Journal of Preventive Medicine*. 2021;61(3): 434–438.
29. Eruchalu CN, Pichardo MS, Bharadwaj M, et al. The expanding digital divide: digital health access inequities during the COVID-19 pandemic in New York City. *Journal of Urban Health*. 2021;98(2): 183–186.
30. Pew Research Center. Mobile fact sheet. Pew Research Center Internet & Technology website. 2021. https://www.pewresearch.org/internet/fact-sheet/mobile/
31. Rodriguez JA, Clark CR, Bates DW. Digital health equity as a necessity in the 21st Century Cures Act era. *Journal of the American Medical Association*. 2020;323(23): 2381–2382.
32. Fitzpatrick L, Skilla N. The digital divide in healthcare: It's. not just access. HIMSS. 2021. https://www.himss.org/resources/digital-divide-healthcare-its-not-just-access
33. Yang R, Zeng K, Jiang Y. Prevalence, factors, and association of electronic communication use with patient-perceived quality of care from the 2019 Health Information National Trends Survey 5-Cycle 3: exploratory study. *Journal of Medical Internet Research*. 2022;24(2): e27167.
34. Yao R, Zhang W, Evans R, Cao G, Rui T, Shen L. Inequities in health care services caused by the adoption of digital health technologies: scoping review. *Journal of Medical Internet Research*. 2022;24(3): e34144.
35. Vogels EA. Some digital divides persist between rural, urban and suburban America. Pew Research Center. 2021. https://www.pewresearch.org/fact-tank/2021/08/19/some-digital-divides-persist-between-rural-urban-and-suburban-america/
36. Vaportzis E, Clausen MG, Gow AJ. Older adults perceptions of technology and barriers to interacting with tablet computers: a focus group study. *Frontiers in Psychology*. 2017;8: 1687.
37. Xu H. Tablet application GUI usability checklist—creation of a user interface usability checklist for tablet applications. Sodertons Hogskola. 2012. https://www.diva-portal.org/smash/get/diva2:629028/FULLTEXT01.pdf
38. Grudz A, Staves K, Wilk A. Connected scholars: examining the role of social media in research practices of faculty using the UTAUT model. *Computers in Human Behavior*. 2012;28(6): 2340–2350.
39. Kaba B, Touré B. Understanding information and communication technology behavioral intention to use: applying the UTAUT model to social networking site adoption by young people in a least developed country. *Journal of the Association for Information Science and Technology*. 2014;65(8): 1662–1674.

40. Nguyen GT. Challenges and opportunities in the care of Asian American patients. *American Family Physician*. 2014;90(7): 490–494.

41. Spencer MS, Chen J, Gee GC, Fabian CG, Takeuchi DT. Discrimination and mental health–related service use in a national study of Asian Americans. *American Journal of Public Health*. 2010;100(12): 2410–2417.

42. Adia AC, Nazareno J, Operario D, Ponce NA. Health conditions, outcomes, and service access Among Filipino, Vietnamese, Chinese, Japanese, and Korean adults in California, 2011-2017. *American Journal of Public Health*. 2020;110(4): 520–526.

43. Hood KK, Wong JJ. Telehealth for people with diabetes: poised for a new approach. *The Lancet. Diabetes & Endocrinology*. 2022;10(1): 8–10.

44. Griffin AC, Chung AE. Health tracking and information sharing in the patient-centered era: a Health Information National Trends Survey (HINTS) Study. *AMIA Annual Symposium Proceeding/AMIA Symposium*. 2020;2019: 1041–1050.

45. Iott BE, Campos-Castillo C, Anthony DL. Trust and privacy: how patient trust in providers is related to privacy behaviors and attitudes. *American Medical Informatics Association Annual Symposium Proceedings*. 2020;2019: 487–493.

46. Booth RG, Strudwick G, McBride S, O'Connor S, Solano López AL. How the nursing profession should adapt for a digital future. *BMJ*. 2021;373: n1190.

47. Brennan PF, Bakken S. Nursing needs big data and big data needs nursing. *Journal of Nursing Scholarship*. 2015;47: 477–484.

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