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The use of self-monitoring modalities to promote health behavior among adults: A cross-sectional survey

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ABSTRACT

Background: U.S. adults experience challenges in performing and sustaining healthy behaviors to improve their cardiovascular health. Self-monitoring modalities may facilitate these lifestyle changes. Therefore, the objective of this cross-sectional study was to examine the use of self-monitoring modalities and the association between the use of multiple self-monitoring modalities and participants' population characteristics, health behaviors, and status.

Methods: Data were drawn for the Health Information National Trends Survey 5, Cycle 1. The study included 3,285 U.S. adults, 18 years or older. Descriptive statistics examined the use of different types of self-monitoring modalities. Binary and ordered logistic regression analyses examined the relationship between the types of self-monitoring modalities and participants' population characteristics, health behaviors, and status. Tableau Software was used to illustrate study results.

Results: The average age of participants was 54.3 years. Smartphone/tablet users were more likely to have completed college (45.28%) compared to electronic monitoring device users (41.06%) and online medical record users (34.04%). Among smartphone/tablet users, participants had significantly higher odds of consuming >4 cups of fruits/vegetables than ≤4 cups of fruits/vegetables [odds ratio (OR) = 2.27, 95 confidence interval (CI) = 1.32–3.90]. An increase in the number of self-monitoring modalities used was associated with a higher odds of participants consuming >4 cups of fruits/vegetables compared to participants who consumed ≤4 cups of fruits/vegetables (OR = 1.76, 95% CI = 1.13–2.76).

Conclusions: Findings of this study highlight that U.S. adults are utilizing a variety of modalities to monitor their health. Several self-monitoring modalities were associated with consuming the recommended amount of fruits/vegetables and performing moderate physical activity for >150 minutes/week. Further research is warranted to understand how to utilize population characteristics, health behavior, and status to promote the efficacy of self-monitoring.

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Introduction

The exponential evolution of digital health has fostered the development of ample technology-based strategies for cardiovascular health (CVH) promotion. These technological innovations are pertinent and timely as cardiovascular disease (CVD) continues to be a burden among U.S. adults. According to the Centers for Disease Control and Prevention, one in four deaths each year is due to CVD [1]. Moreover, the World Health Organization highlights that more than 80% [2] of premature CVD mortalities can be prevented.

The literature illustrates that CVD deaths can be prevented by promoting ideal CVH among adults yet

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current statistics indicate that a substantial number of U.S. adults have non-ideal CVH. Approximately, 87.9% do not consume the recommended cups of fruit and vegetables, 70.4% have a body mass index (BMI) over 25 kg/m^2, 63.3% do not perform recommended physical activity (PA), and 22.9% of U.S. adults are smokers [3]. This study discusses how encouraging adults to use self-monitoring modalities may have significant implications on promoting positive CVH behaviors. Specifically, monitoring one's diet and PA can help individuals lower their BMI, and in turn, reduce their blood pressure (BP), as research has shown that losing more than 5% of one's body weight can lower one's BP level [4]. The positive effects of self-monitoring modalities on CVH promotion is supported by current research that found individuals with mobile phone health apps were more likely to report having intentions to increase fruit and vegetable consumption, lose weight, as well as meet recommendations for PA [5].

Health apps are a ubiquitous type of digital health promotion technology, as more than 325,000 [6] health apps were available to download via a smartphone and/or tablet in 2017. In a national survey conducted on the use of health apps among mobile phone owners, over half (58%) of participants has downloaded a health-related app [7]. It was also reported that among those who had downloaded mobile health apps, trust in accuracy of data was high [7]. Electronic health records are another potential health promotion modality that can shape patient education and facilitate self-monitoring of one's health. The current adoption rate of an online medical record (OMR) system by healthcare settings has led to more than 50% of U.S. adults being offered access to their OMR and more than half of OMR users viewing their record at least once in 2017 [8]. Research also shows that in 2015, more than 41% of OMRs allowed patients to download their records, nearly 19% transmitted patient records, and approximately 16% allowed patients to view, download, and transmit their health information [9]. These engagement capabilities of OMRs help increase their use among individuals, and thus may, increase self-monitoring. Electronic monitoring devices (EMDs), such as wearable devices (e.g., Fitbit) and BP and glucose monitoring devices, have been widely accepted among the general public and are also used for self-monitoring [10–12].

Several studies have been performed to determine the appropriate content of self-monitoring modalities Specifically, these studies identified health behaviors people have sought to change, and to determine the effectiveness of these methods [5,13–15]. However, little is known about the users of these self-monitoring modalities (use of smartphone/tablet, OMR, or EMDs). Additionally, there are gaps in the literature on the current health status of self-monitoring modality users, specifically their CVH, and their use of multiple self-monitoring modalities. EMDs are associated with health apps [13], and several healthcare systems are beginning to connect OMRs to health apps [16–18]. These advancements enable the use of more than one self-monitoring modality to monitor one's health. Hence, obtaining a foundational understanding of the users and the use of multiple methods may aid in understanding barriers to their use and the development of interventions that increase the adoption of their use. The aforementioned gaps in the literature guided the objectives of this study, which were to examine the use of self-monitoring modalities and the association between the use of multiple self-monitoring modalities and participants' population characteristics, health behaviors, and status.

Methodology

Design

The Health Information National Trends Survey (HINTS) is a nationally-representative survey administered by the National Cancer Institute to U.S. civilians that are 18 years and older and not institutionalized [19]. The survey inquires about health behavior, access to care, and healthcare services [19]. HINTS 5, Cycle 1 was collected from January 2017 to May 2017, yielding a 32.39% response rate. The Behavioral Model of Health Services Use [20] guided model fitting, as environment (i.e., have self-monitoring modality), population characteristics and health behaviors, and status can influence the use of self-monitoring modalities to improve health outcomes.

Measures

Dependent variables

The three dependent variables in this study were as follows: (1) use of OMR to monitor health, *In the past 12 months, have you used your online medical record to monitor your health?*; (2) use of smartphone/tablet to monitor health, *Has your tablet or smartphone helped you track progress on a health-related goal such as quitting smoking, losing*

weight, or increasing physical activity?; and (3) use of EMD, *Other than a tablet or smartphone, have you used an electronic device to monitor or track your health within the last 12 months? Examples include Fitbit, blood glucose meters, and blood pressure monitors.* Participants provided a yes/no response to the preceding variables. The percentage of missing values for the three dependent variables due to missing data, participant error in answering a question, and/or questions being inapplicable to participants, was less than 15%. Therefore, the missing responses for the three dependent variables were excluded from the final analyses. To examine the use of multiple self-monitoring modalities, the three dependent variables were combined to create a new variable: multiple self-monitoring, with the responses of 0 = use none of the three modalities, 1 = use one of the three modalities, 2 = use two of the three modalities, and 3 = use all three modalities. It should be noted that the questionnaire did not provide insight as to how or what component of participants' health (e.g., PA) was monitored using the respective modalities.

Independent variables

Population characteristics:

Various population characteristics were examined in the survey, including age (in years), gender (male/female), health insurance status (coverage/no coverage), whether one was born in the U.S. (yes/no), and have family or friends to talk about health with (yes/no). Race/ethnicity was recategorized to White, Black, Hispanic, or Other (Other race or Asian). Similarly, participants' marital status was recoded to married, divorced, single, or other (living as married, widowed, or separated). Education was reclassified to less than high school/high school graduate, some college, and college degree or more. Household income was categorized as <$20,000, $20,000–<$35,000, $35,000–<$50,000, and $50,000–<$75,000, and >$75,000.

Additionally, the 2013 rural/urban designation variable was included but underwent recategorization to address the limited number of observations. Participants who reported living in a metropolitan area were combined and every participant who reported living in a nonmetropolitan area was grouped together to create the dichotomous variable: metropolitan versus nonmetropolitan status. Participants' knowledge of providers' encouragement of the use of OMR (yes/no) was also assessed. Perception of the usefulness of OMRs to monitor health was included and recoded to very useful, somewhat useful, and not very/not at all useful.

Participants were also asked whether they have a regular provider (yes/no) and whether they have family or friends to talk about health with (yes/no). Perceived health was recoded to excellent, very good, good, and fair/poor. The variable "confidence in ability to take care of one's health" was recoded to completely confident, very confident, somewhat confident, and little/not at all confident.

Health behaviors and status

Participants' smoking status (never, former, or current) was examined. Additional health behaviors were derived to reflect the American Health Association (AHA) recommendations for ideal CVH [21]. Specifically, in the survey, fruit and vegetable intake were two separate questions; *About how many cups of fruit do you eat or drink each day?* and *About how many cups of vegetables do you eat or drink each day?*, with the response options of none, ½ cup or less, ½ cup-1 cup, 1–2 cups, 2–3 cups, 3–4 cups, and 4 or more cups. Responses to both the questions were combined to create the fruit/vegetable variable, with the responses of ≤4 cups and >4 cups of fruits/vegetables. Similar classifications of ideal CVH *versus* non-ideal CVH was utilized for PA (≥150 minutes/week moderate intensity *vs.* <150 minutes/week moderate intensity), which was created based upon participants' responses to questions regarding the number of days they perform moderate PA or exercise per week (0–7 days) and the length of time they perform moderate PA or exercise (0–90 minutes); participants' responses to these two questions were multiplied to obtain the total minutes of moderate exercise performed each week. BMI [(Weight*703)/(Height in inches**2)] was also re-categorized to <25 kg/m^2 *versus* ≥25 kg/m^2 to reflect the AHA's classification of ideal CVH [21].

The models also included participants' responses to whether a health provider has ever told them they had high BP, diabetes, or a heart condition, with each of these questions having a yes/no response. Participants' Patient Health Questionnaire-4 [22] (PHQ-4) score (0–12), derived from participants' responses to how often they feel little interest, hopeless, nervous, and worrying, was recategorized to not at all *versus* experiencing any of the preceding emotions several days, more than half the days, or nearly every day. Digital health-related behavior questions were incorporated including, have you used the internet in the last 12 months

to: (1) share health information on a social networking site; (2) participate in a forum/support group for a medical issue; (3) watch a health-related video on YouTube; or (4) write in an online diary/blog, with each question containing a yes/no response. Participants' health information-seeking behavior was included in using the variable "ever looked for health/medical information (yes/no)."

To ensure the quality of the data, HINTS staff scanned the questionnaires using TeleForm software, and they verified and edited the data [23]. Data editing was performed for two variables of interest in this study to address invalid or unusual values. These variables were height of participant in inches and number of minutes performing moderate exercise weekly [23]. Additional details regarding data collection, management, and cleaning of HINTS 5, Cycle 1 can be found on HINTS' website [23].

Analysis

For this cross-sectional study, descriptive statistics were conducted to examine participants' population characteristics, health behavior, and status across different self-monitoring modalities and the use of multiple modalities. Tableau Software visualized fruit/vegetable intake, PA level, and BMI status by self-monitoring modality. Sample-weighted binary logistic regression analyses, using the jackknife method, were performed to examine the odds of using self-monitoring modalities by participants' population characteristics, health behavior, and status. Model fit was evaluated using Hosmer–Lemeshow statistic [24]. Sample-weighted ordered logistic regression analyses were also performed to examine the odds of using multiple self-monitoring modalities by participants' population characteristics, health behavior, and status. All the analyses were performed using STATA/MP version 14 [25].

Results

Use of self-monitoring modalities

The sample consisted of 3,285 U.S. adults in which the average age of the participants was 54.3 years (SD = 15.23), and the majority were female (60%) (Table 1). Females were more likely to use a smartphone/tablet (39.4%) to monitor their health than to use an EMD (35.80%) or OMR (33.53%).

Use of multiple self-monitoring modalities

Findings of the study show that 23.79% of U.S. adults reported using none of the self-monitoring modalities, 31.83% stated that they used one method, 30.62% reported using two methods, and 13.77% reported using all the three methods (Fig. 1). In assessing health behaviors by self-monitoring modality, 11.58% of all the users met recommendations for fruit/vegetable intake, PA, and BMI status (Fig. 2).

Relationship between self-monitoring modalities and participants' population characteristics, health behaviors, and status

Among smartphone/tablet users, female participants were 2.04 times more likely than their male counterparts to report using a smartphone/tablet to monitor their health [95% confidence interval (CI) = 1.03–4.06] (Table 2). Smartphone/tablet users with a BMI ≥25 kg/m^2 were 2.72 times more likely than those with a BMI <25 kg/m^2 to report using a smartphone/tablet to monitor their health (95% CI = 1.32–5.61). Additionally, among smartphone/tablet users, participants had significantly higher odds of consuming >4 cups of fruits/vegetables compared to those who consumed ≤4 cups of fruits/vegetables [odds ratio (OR) = 2.27, 95 CI = 1.32–3.90].

Similar to smartphone/tablet users, OMR users had higher odds of having a BMI ≥ 25 kg/m^2 than they were to have a BMI < 25 kg/m^2 (OR = 2.07, 95% CI = 1.14–3.74). Users who used an EMD were significantly more likely to have some college education (OR = 2.82, 95% CI = 1.09–7.29) than they were to have no college education/less than a high school education.

Association between multiple self-monitoring modalities and participants' population characteristics, health behaviors, and status

Each unit increase in the number of self-monitoring modalities used was associated with a higher odds of adults consuming >4 cups of fruits/vegetables compared to adults who consumed ≤4 cups of fruits/vegetables (OR = 1.76, 95% CI = 1.13–2.76) (Table 3). Additionally, an increase in the number of self-monitoring modalities used was associated with a higher odds of participants performing ≥150 minutes of moderate PA per week compared to the odds of participants performing <150 minutes/week of moderate PA (OR = 1.94, 95% CI = 1.17–3.20).

Table 1. Unweighted characteristics of participants, 3,285.

Population characteristics	Smartphone/Tablet *n* = 2,685		Electronic monitoring device *n* = 3,249		Online medical record *n* = 978	
	Yes	No	Yes	No	Yes	No
	n (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)
Age in years, Mean (SD)	47.92 (14.34)	57.37 (15.15)	56. 86 (15.58)	55.93 (16.39)	53.12 (14.84)	54.60 (15.10)
Gender	981 (37.19)	1,657 (62.81)	1,162 (36.48)	2,023 (63.52)	321 (33.23)	645 (66.77)
Male	360 (33.80)	705 (66.20)	485 (37.48)	809 (62.52)	129 (36.13)	228 (63.87)
Female	621 (39.48)	952 (60.52)	677 (35.80)	1,214 (64.20)	192 (31.53)	417 (68.47)
Race/ethnicity						
White	566 (36.66)	978 (63.34)	709 (38.2)	1,147 (61.8)	206 (31.69)	444 (68.31)
Black	143 (41.94)	198 (58.06)	151 (37.28)	254 (62.72)	40 (42.55)	54 (57.45)
Hispanic	138 (38.33)	222 (61.67)	126 (29.79)	297 (70.21)	25 (28.74)	62 (71.26)
Other	91 (41.74)	127 (58.26)	95 (38.46)	152 (61.54)	32 (35.56)	58 (64.44)
Education Level	980 (37.46)	1,636 (62.54)	1,153 (36.61)	1,996 (63.39)	320 (33.37)	639 (66.63)
Less than High/High school	141 (25.31)	416 (74.69)	223 (27.29)	594 (72.71)	39 (29.77)	92 (70.23)
Some college	258 (33.25)	518 (66.75)	356 (38.12)	578 (61.88)	87 (33.72)	171 (66.28)
College grad or more	581 (45.28)	702 (54.72)	574 (41.06)	824 (58.94)	194 (34.04)	376 (65.96)
Marital status						
Married	601 (41.02)	864 (58.98)	685 (41.67)	959 (58.33)	205 (33.72)	403 (66.28)
Divorced	127 (34.32)	243 (65.68)	151 (31.33)	331 (68.67)	42 (31.34)	92 (68.66)
Single	70 (40.28)	252 (59.72)	139 (27.58)	365 (72.42)	41 (33.88)	80 (66.12)
Other- Living, Widowed, Separated	75 (21.87)	268 (78.13)	174 (34.66)	328 (65.34)	29 (32.22)	61 (67.78)
Perceived health	985 (37.04)	1,674 (62.96)	1,165 (36.26)	2,048 (63.74)	324 (33.3)	649 (66.7)
Excellent	147 (45.23)	178 (54.77)	111 (31.01)	247 (68.99)	40 (34.78)	75 (65.22)
Very good	430 (42.24)	588 (57.76)	414 (35.6)	749 (64.4)	138 (32.24)	290 (67.76)
Good	295 (32.89)	602 (67.11)	417 (37.3)	701 (62.7)	100 (33.78)	196 (66.22)
Fair/poor	113 (26.97)	306 (73.03)	223 (38.85)	351 (61.15)	46 (34.33)	88 (65.67)
Health Behaviors and Status						
BMI	992 (36.95)	1, 693 (63.05)	1,178 (36.26)	2,071 (63.74)	325 (33.23)	653 (66.77)
<25 kg/m^2	323 (37.82)	531 (62.18)	328 (31.42)	716 (68.58)	89 (26.65)	245 (73.35)
≥25 kg/m^2	669 (36.54)	1,162 (63.46)	850 (38.55)	1,355 (61.45)	236 (36.65)	408 (63.35)
Smoking status	988 (37.09)	1,676 (62.91)	1,173 (36.42)	2,048 (63.58)	324 (33.3)	649 (66.7)
Current	95 (29.05)	232 (70.95)	100 (24.39)	310 (75.61)	19 (23.17)	63 (76.83)
Former	260 (37.25)	438 (62.75)	337 (39.6)	514 (60.4)	90 (32.03)	191 (67.97)
Never	633 (38.62)	1,006 (61.38)	736 (37.55)	1,224 (62.45)	215 (35.25)	395 (64.75)
Fruit/Vegetable Consumption	976 (37.08)	1,656 (62.92)	1,150 (36.22)	2,025 (63.78)	322 (33.4)	642 (66.6)
>4 cups	468 (43.62)	605 (56.38)	494 (39.3)	763 (60.7)	153 (36.26)	269 (63.74)
≤4 cups	508 (32.58)	1,051 (67.42)	656 (34.2)	1,262 (65.8)	169 (31.18)	373 (68.82)
Physical activity	992 (36.95)	1,693 (63.05)	1,178 (36.26)	2,071 (63.74)	325 (33.23)	653 (66.77)
<150 minutes/week	502 (32.37)	1,049 (67.63)	670 (35.04)	1,242 (64.96)	177 (32.12)	374 (67.88)
≥150 minutes/week	490 (43.21)	644 (56.79)	508 (38)	829 (62)	148 (34.66)	279 (65.34)

Discussion

This is the first study to examine the users across different types of self-monitoring modalities and the use of multiple self-monitoring modalities. Among adults that used one self-monitoring modality, EMDs were most commonly utilized. Findings of this study also show that more than 44% of participants reported using two or more of the self-monitoring modalities, with smartphone/tablet and EMD

being the most frequently combined methods. This finding was not surprising as the literature alludes to the growing popularity in the use and pairing of smartphones/tablets and EMDs to engage adults in health promotion activities [13], as well as the use of EMDs to assist with chronic condition management [26,27].

Several population characteristics were significantly associated with smartphone/tablet use. As age increased, the odds of using a smartphone/tablet significantly decreased. This finding reflects the previous research that show older individuals experience challenges in incorporating technology into their lifestyle [15]. Factors, such as familiarity with device and access to modalities, have been found to influence this relationship [12]. A growing body of literature highlights that older individuals are interested in utilizing these modalities [12,28], and the implications of changing and improving health behaviors can be significant, as older populations are inclined to have a higher CVD risk [29]. A significant relationship was also found between gender and smartphone/tablet use. Females had twice the odds of using a smartphone/tablet to monitor their health compared to their male counterparts. Previous research has found that males have lower odds of adopting the use of health apps [29], which also coincides with the ample literature that indicate men have lower confidence in managing their health [30,31].

A limited number of characteristics were associated with using an EMD. These findings were expected because the definition of an EMD was broad and ranged from the use of wearable devices (e.g., Fitbit) to BP monitoring devices. This definition might have limited the understanding of these users.

In examining the results of the binary and ordered logistic regression analyses, BMI was found to be significantly associated with the use of a smartphone/tablet, OMR, and multiple self-monitoring modalities. This is similar to the outcomes of previous research that found health app users to be obese [7]. First, it should be noted that there is limited to no insight on how long the apps were used to understand its impact on BMI level. This relationship may also be in part explained by U.S. adults having a disproportionate balance between energy intake and expenditure [32]. Specifically, their energy intake may be more than their energy expenditure [32], resulting in them having a high BMI despite using a self-monitoring modality. Further research should be performed to determine

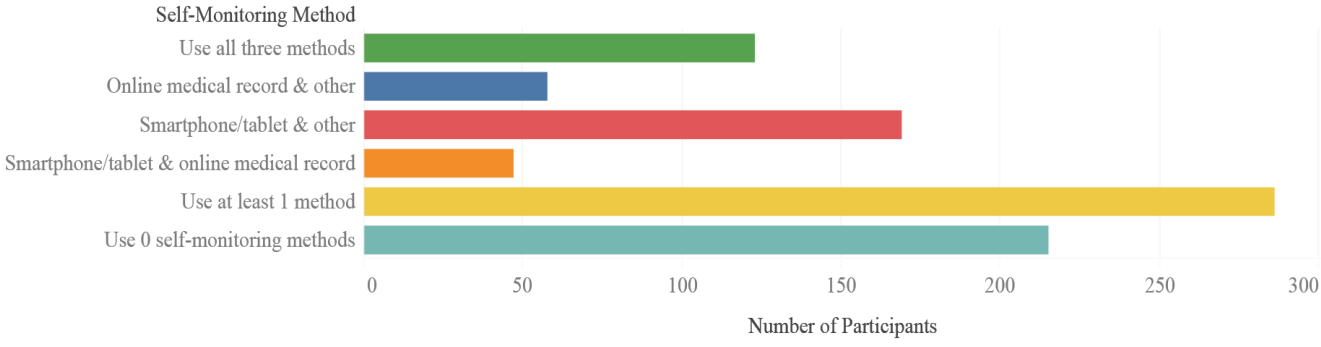

Figure 1. Illustration of the use of one or more self-monitoring modalities.

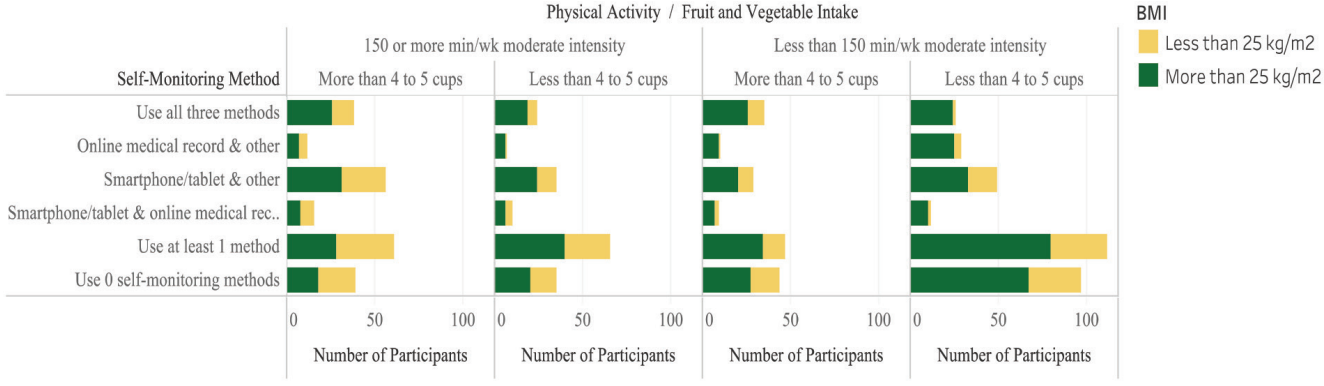

Figure 2. Visualization of fruit/vegetable intake, physical activity level, and BMI status by self-monitoring modalities.

Table 2. Relationship between self-monitoring modalities and participants' population characteristics, health behaviors, and status.

	Smartphone/Tablet			Online medical record			Electronic monitoring device		
	Odds ratio	95% CI	*p*-value	Odds ratio	95% CI	*p*-value	Odds ratio	95% CI	*p*-value
Population Characteristics									
Age (Years)	0.97	0.94–0.99	0.002	0.99	0.96–1.02	0.48	1.00	0.98–1.03	0.73
Gender									
Male (Reference)									
Female	2.04	1.03–4.06	0.04	0.60	0.32–1.13	0.11	0.81	0.45–1.48	0.49
Race/ethnicity									
White (Reference)									
Black	0.74	0.21–2.61	0.64	0.67	0.25–1.79	0.42	0.86	0.34–2.15	0.73
Hispanic	1.19	0.39–3.63	0.75	0.98	0.28–3.40	0.98	0.85	0.37–1.97	0.70
Other	1.32	0.62–2.82	0.46	0.96	0.34–2.75	0.94	1.19	0.50–2.84	0.68
Education level									
Less than High/ High school graduate (Reference)									
Some college	1.00	0.30–3.33	1.00	1.64	0.73–3.66	0.23	2.82	1.09–7.29	0.03
College graduate or more	1.25	0.41–3.82	0.69	2.18	0.91–5.18	0.08	1.45	0.55–3.84	0.45
Marital status									
Married (Reference)									
Divorced	0.86	0.34–2.15	0.74	1.28	0.49–3.33	0.61	0.77	0.31–1.95	0.58
Single	0.60	0.22–1.60	0.30	0.98	0.34–2.83	0.96	0.68	0.29–1.57	0.36
Other	1.52	0.61–3.79	0.36	1.12	0.50–2.55	0.78	1.58	0.61–4.05	0.34
Household income									
Less than $20,000	0.44	0.15–1.31	0.14	0.44	0.14–1.39	0.16	0.47	0.06–3.62	0.46
$20,000 to < $35,000	0.45	0.14–1.47	0.18	1.13	0.36–3.55	0.83	0.42	0.14–1.25	0.12
$35,000 to < $50,000	0.72	0.27–1.93	0.50	1.01	0.34–3.00	0.99	0.36	0.15–0.83	0.02
$50,000 to < $75,000	0.74	0.39–1.38	0.33	1.30	0.75–2.25	0.35	0.48	0.22–1.05	0.07
$75,000 or More (Reference)									
Rural/Urban Designation									
Metropolitan (Reference)									
Non-metropolitan	0.95	0.32–2.80	0.93	3.47	1.43–8.43	0.01	1.05	0.37–2.99	0.93
Born in the USA									
No (Reference)									
Yes	1.47	0.63–3.41	0.37	0.47	0.21–1.04	0.06	2.11	0.96–4.66	0.06
Health Behaviors and Status									
PHQ4 status									
Did not feel hopeless, nervous, or had little interest (Reference)									
Felt hopeless, nervous, or had little interest	0.98	0.52–1.84	0.95	0.88	0.51–1.54	0.66	1.20	0.70–2.03	0.50

Continued

	Smartphone/Tablet			Online medical record			Electronic monitoring device		
	Odds ratio	95% CI	*p*-value	Odds ratio	95% CI	*p*-value	Odds ratio	95% CI	*p*-value
Have a regular provider									
No (Reference)									
Yes	1.05	0.52–2.13	0.89	1.33	0.57–3.08	0.50	1.80	0.80–4.04	0.15
Talk to friends about health									
No (Reference)									
Yes	2.39	0.82–6.93	0.11	2.65	0.75–9.35	0.13	0.96	0.34–2.72	0.93
Perceive health									
Excellent (Reference)									
Very good	0.96	0.40–2.32	0.92	0.67	0.27–1.64	0.37	1.49	0.61–3.61	0.37
Good	0.57	0.19–1.68	0.30	0.66	0.23–1.86	0.42	2.10	0.65–6.75	0.21
Fair/poor	0.77	0.22–2.67	0.67	0.79	0.18–3.47	0.75	1.39	0.31–6.16	0.66
Confidence in managing health									
Completely confident (Reference)									
Very confident	1.50	0.82–2.77	0.19	0.92	0.46–1.83	0.81	1.06	0.52–2.18	0.87
Somewhat confident	1.74	0.64–4.74	0.28	0.72	0.29–1.78	0.47	1.28	0.40–4.08	0.67
A little/not at all confident	2.05	0.36–11.75	0.42	1.34	0.29–6.15	0.70	1.09	0.13–9.28	0.94
Fruit/vegetables consumption									
≤4 cups (Reference)									
>4 cups	2.27	1.32–3.90	0.004	0.99	0.57–1.73	0.97	1.83	0.95–3.51	0.07
Physical activity									
<150 minutes/week (Reference)									
≥150 minutes/week	2.32	1.32–4.07	0.004	0.99	0.54–1.80	0.97	1.71	0.94–3.13	0.08
Smoking status									
Current (Reference)									
Former	0.49	0.16–1.49	0.20	1.63	0.52–5.13	0.40	0.98	0.26–3.67	0.97
Never	0.41	0.16–1.06	0.07	2.15	0.79–5.88	0.13	1.07	0.35–3.26	0.91
BMI status									
<25 kg/m^2 (Reference)									
≥25 kg/m^2	2.72	1.32–5.61	0.01	2.07	1.14–3.74	0.02	1.29	0.64–2.57	0.47
Ever seek health information									
No (Reference)									
Yes	1.95	0.78–4.92	0.15	1.89	0.70–5.13	0.21	0.73	0.26–2.05	0.54
Provider ever told you have high blood pressure									
No (Reference)									
Yes	0.75	0.35–1.57	0.44	1.50	0.79–2.83	0.21	1.61	0.86–3.01	0.14
Provider ever told you have a heart condition									
No (Reference)									
Yes	1.23	0.45–3.37	0.68	0.50	0.18–1.39	0.18	1.28	0.30–5.49	0.73
Provider ever told you have diabetes									
No (Reference)									
Yes	1.54	0.59–3.99	0.37	1.81	0.76–4.29	0.18	1.62	0.64–4.09	0.31

Continued

	Smartphone/Tablet			Online medical record			Electronic monitoring device		
	Odds ratio	95% CI	*p*-value	Odds ratio	95% CI	*p*-value	Odds ratio	95% CI	*p*-value
Provider encouraged use of online medical record									
No (Reference)									
Yes	0.88	0.38–2.02	0.76	2.34	0.96–5.70	0.06	0.90	0.39–2.07	0.80
Past 12 months watched a health-related video on YouTube									
No (Reference)									
Yes	2.64	1.50–4.65	0.001	1.40	0.77–2.56	0.27	1.36	0.82–2.24	0.23
Past 12 months participated in a forum/support group for medical issue									
No (Reference)									
Yes	1.36	0.52–3.57	0.53	1.59	0.70–3.61	0.26	2.04	0.97–4.30	0.06
Past 12 months shared health information on social networking site									
No (Reference)									
Yes	1.37	0.65–2.85	0.40	1.06	0.47–2.42	0.88	1.74	0.72–4.20	0.22
Past 12 months write in an online diary or blog									
No (Reference)									
Yes	3.55	1.09–11.63	0.04	1.09	0.33–3.59	0.88	0.59	0.22–1.58	0.29
Perceive usefulness in using online medical record to monitor health									
Very useful (Reference)									
Somewhat useful	1.05	0.60–1.86	0.86	0.25	0.15–0.40	<0.001	0.97	0.54–1.73	0.91
Not very/not at all	0.76	0.28–2.01	0.57	0.17	0.03–0.90	0.04	0.87	0.36–2.15	0.77

if self-monitoring modalities are being used to inform adults of their recommended energy intake and assist them in balancing their energy.

A positive relationship was also found between fruit/vegetable consumption and PA and using a smartphone/tablet and/or multiple modalities. Specifically, participants that used a smartphone/tablet and/or multiple modalities to monitor their health had higher odds of meeting the fruit/vegetable and PA recommendations. Previous studies [5,15,33] have observed this relationship, which may be associated with users of self-monitoring approaches having a higher determination to change their behaviors compared to that of non-self-monitoring modality users [5,34]. Additional research should be performed to further understand factors (e.g., higher determination to change behaviors) that may influence this relationship.

As the number of self-monitoring modalities used increased, the odds of participants perceiving an OMR as somewhat useful decreased. The lack of perceived usefulness may be associated with challenges in navigating the OMR and understanding medical information in OMRs [35–37]. Another potential reason is patients' preference to speak directly with their provider [8,38]. The Office of the National Coordinator for Health Information Technology's 2018 data brief indicate that in 2017, 76% of U.S. adults who did not access their OMR in the past year attributed the reason to their preference for speaking directly to their provider [8]. This theory has also been supported by earlier research that discusses the role of OMR on the provider–patient relationship [38].

Limitations

The following limitations should be considered. First, this study shows that U.S. adults are using self-monitoring modalities; however, it does not provide specific details on the features or instructions provided by the modalities. Second, although this survey contains a nationally representative sample of U.S. adults, a lower response rate was identified among rural and minority individuals, which may result in the over- or under-estimation of the use of self-modalities among these populations. Third, HINTS data is self-reported; therefore, it is subject to recall bias. Lastly, this is a cross-sectional study, which prevents the determination of causal inferences.

Table 3. Multiple self-monitoring modalities and participants' population characteristics, health behaviors, and status.

	Odds ratio	95% CI	*p*-value
Population characteristics			
Age (Years)	0.98	0.96-1.00	0.13
Gender			
Male (Reference)			
Female	0.98	0.56-1.71	0.95
Race/ethnicity			
White (Reference)			
Black	0.79	0.25-2.47	0.68
Hispanic	1.05	0.55-2.00	0.89
Other	1.31	0.57-3.00	0.52
Education level			
Less than High/High school graduate (Reference)			
Some college	2.02	0.91-4.46	0.08
College graduate or more	1.65	0.72-3.80	0.23
Marital status			
Married (Reference)			
Divorced	1.01	0.45-2.29	0.97
Single	0.62	0.29-1.35	0.22
Other	1.62	0.70-3.76	0.25
Household income			
Less than $20,000	0.48	0.12-1.94	0.30
$20,000 to < $35,000	0.51	0.21-1.27	0.15
$35,000 to < $50,000	0.49	0.21-1.12	0.09
$50,000 to < $75,000	0.76	0.41-1.43	0.39
$75,000 or More (Reference)			
Rural/Urban Designation			
Metropolitan (Reference)			
Nonmetropolitan	1.96	0.80-4.80	0.14
Born in the USA			
No (Reference)			
Yes	1.15	0.53-2.53	0.72
Health behaviors and status			
Fruit/vegetables consumption			
≤4 cups (Reference)			
>4 cups	1.76	1.13-2.76	0.01
Physical activity			
<150 minutes/week (Reference)			
≥150 minutes/week	1.94	1.17-3.20	0.01
Smoking status			
Current (Reference)			
Former	0.89	0.31-2.55	0.82
Never	0.98	0.43-2.25	0.97
BMI status			
<25 kg/m^2 (Reference)			

Continued

	Odds ratio	95% CI	*p*-value
≥25 kg/m^2	2.30	1.23-4.30	0.01
PHQ4 status			
Did not feel hopeless, nervous, or had little interest (Reference)			
Felt hopeless, nervous, or had little interest	0.98	0.61-1.57	0.94
Have a regular provider			
No (Reference)			
Yes	1.35	0.67-2.70	0.40
Ever seek health information			
No (Reference)			
Yes	1.41	0.65-3.06	0.38
Talk to friends about health			
No (Reference)			
Yes	2.26	1.12-4.57	0.02
Perceive health			
Excellent (Reference)			
Very good	0.86	0.39-1.88	0.69
Good	0.81	0.28-2.37	0.70
Fair/poor	0.80	0.23-2.74	0.71
Confidence in managing health			
Completely confident (Reference)			
Very confident	1.35	0.73-2.48	0.33
Somewhat confident	1.41	0.46-4.29	0.54
A little/not at all confident	2.13	0.38-11.97	0.38
Provider ever told you have high blood pressure			
No (Reference)			
Yes	1.21	0.65-2.25	0.55
Provider ever told you have a heart condition			
No (Reference)			
Yes	0.82	0.34-1.99	0.66
Provider ever told you have diabetes			
No (Reference)			
Yes	1.99	0.93-4.28	0.08
Provider encouraged use of online medical record			
No (Reference)			
Yes	1.44	0.69-3.02	0.32
Perceive usefulness in using online medical record to monitor health			
Very useful (Reference)			
Somewhat useful	0.57	0.36-0.90	0.02
Past 12 months watched a health-related video on YouTube			
No (Reference)			
Yes	1.83	1.17-2.87	0.01
Past 12 months participated in a forum/support group for medical issue			

Continued

	Odds ratio	95% CI	*p*-value
No (Reference)			
Yes	1.70	0.83-3.45	0.14
Past 12 months shared health information on social networking site			
No (Reference)			
Yes	1.43	0.73-2.80	0.29
Past 12 months write in an online diary or blog			
No (Reference)			
Yes	1.10	0.52-2.33	0.81

Conclusion

The findings of this study highlight that various modalities can be used in targeted interventions to promote behavior change among U.S. adults. Specifically, positive health behaviors, such as consuming recommended fruits/vegetables and meeting guidelines for moderate PA, were associated with the use of a smartphone/tablet and/or multiple modalities. Further research should be performed to identify the factors that influence this relationship. In contrast, individuals that utilized a smartphone/tablet and/or EMD were found to have a BMI ≥25 kg/m^2. Additional studies should be performed to determine if self-monitoring modalities are increasing users' awareness of the connection between their energy intake and energy expenditure. This may facilitate users in expending suffice energy for weight loss and help lower BMI levels.

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