The influence of fitness technology use on cancer screening behaviors among American women: Mediation by social media communication and cancer worry (2017–2020)

Yingxia Zhu[1] 🆔, Qingqing Xie[1] 🆔 and Xinshu Zhao[1]

Abstract

Objective: This study investigates how fitness technology (FT) influences cancer screening behaviors among American women, focusing on the role of social media communication and cancer worry as mediators.

Methods: We used data from 9245 women across four cycles (2017–2020) of the Health Information National Trends Survey. Descriptive analyses, one-way ANOVA, and sequential mediation analysis were conducted to assess the relationship between FT use and cancer screening behaviors.

Results: The results indicate that between 2018 and 2020, social media communication and cancer worry sequentially mediated the relationship between FT use and cancer screening behaviors ($b = 0.001/0.001/0.001$, 95% confidence interval (CI) [0.0002, 0.002]/[0.0002, 0.002]/[0.0001, 0.001]). Additionally, there was an upward trend in FT use (from 0.74 in 2017 to 0.93 in 2020), social media communication (from 1.17 in 2017 to 1.39 in 2020), and cancer worry (from 2.60 in 2017 to 2.84 in 2020). However, cancer screening behaviors declined over the same period (from 4.59 in 2017 to 4.35 in 2020).

Conclusion: The study highlights the role of FT in influencing cancer screening behaviors through its impact on social media communication and cancer worry. Despite an increase in FT use, cancer screening behaviors showed a decline, suggesting the need for targeted interventions to bridge this gap and enhance screening behaviors.

Introduction

Cancer remains one of the leading causes of death in the United States,[1] with women particularly at risk for breast and cervical cancers. Breast cancer is the most prevalent type of cancer among women, accounting for approximately 30% of all new female cancer cases annually.[2] Similarly, cervical cancer contributes significantly to cancer-related mortality in women.[1] Given the high mortality risk associated with these cancers, it is essential to promote preventive measures such as regular cancer screenings.

In recent years, fitness technology (FT) has emerged as a tool for promoting health behavior change, especially smartphone applications and wearable devices have demonstrated potential in facilitating various health behaviors,[3–6]

with a primary focus on fitness and self-monitoring.[7] These technologies also offer opportunities for healthcare providers to monitor health metrics, set goals for patients, and support their efforts in achieving behavior change.[8] Data from the United States show that nearly half of smartphone and tablet users have at least one fitness or health-related app installed.[9] Despite the widespread

[1]Department of Communication, University of Macau, Taipa, China

Corresponding author:
Xinshu Zhao, Faculty of Social Sciences (FSS), University of Macau, Avenida da Universidade, Humanities and Social Sciences Building (E21B), 2051, Taipa, China.
Email: xszhao@um.edu.mo

adoption and known benefits of FT,[10–13] existing studies have largely concentrated on its influence on diet and physical activity.[5,14–16] Given that women are significant users of fitness technologies compared to men,[17–20] there remains a gap in understanding how FT affects cancer screening behaviors among women. Understanding this relationship is crucial for enhancing cancer prevention efforts.

Another key factor in influencing health behaviors is social media. According to a 2023 Pew Research Center survey, women are more likely than men to use major social media platforms like YouTube, Facebook, Instagram, and Pinterest.[21] Previous studies have established a positive association between FT use and increased communication on social media, which can lead to health behavior changes.[14] Additionally, research indicates that communication behaviors can alleviate psychological distress, including cancer worry, and may promote cancer screening.[22–24] Despite these findings, the specific roles of social media communication and cancer worry in the relationship between FT use and cancer screening behavior remain unclear.

Given this background, the present study posits that communication behaviors on social media and cancer worry act as sequential mediators between FT use and cancer screening behaviors. To explore this relationship, the study draws on Social Cognitive Theory[25] and the Communication Mediation Model.[26,27] This study aims to: (1) Examine the relationship between FT use and cancer screening behaviors among women; (2) Investigate the sequential mediating roles of social media communication and cancer worry in the link between FT use and cancer screening behaviors and (3) Analyze trends in the relationship between these variables across four years of data from the Health Information National Trends Survey (HINTS) collected in 2017, 2018, 2019, and 2020.

Literature review

FT and cancer screening behaviors

FT, including smartphone applications and wearable devices.[14] Users have the option to select standalone wearable devices, wearable trackers paired with a companion fitness app, or solely use a fitness app on their smartphone or tablet without any additional tracking devices.[28] FT allows to track a range of health-related behaviors, such as weight management, diet monitoring, and sleep tracking.[8,29] These technologies are becoming increasingly popular among women.[18] A Pew Research study revealed that around 25% of women in the United States use a smartwatch or fitness tracker, compared to 18% of men.[18] FT not only enhances their' health knowledge,[30] but has the potential to empower women to take preventive actions, such as undergoing cancer screening, when they perceive themselves at risk.[31,32]

Early detection through cancer screening plays a critical role in reducing cancer mortality.[2,33] Numerous studies emphasize that early detection of breast and cervical cancers significantly increases survival rates,[34–36] and highlight the need to promote screening behaviors among women.[37–40] FT, with features like goal setting, feedback, and tracking, has the potential to motivate users to engage in preventive health behaviors, including cancer screening.[8,28] In fact, 47% of health-related apps focus on managing specific conditions or promoting disease prevention.[41] Research also supports the role of fitness technologies in increasing intentions and actions related to health behaviors,[7,14,42–45] suggesting that FT has the potential to enhance cancer screening behaviors.

The role of social media communication and cancer worry

Social media platforms, such as Facebook, LinkedIn, and YouTube, have become significant venues for health communication.[46] These platforms allow users to share and discuss health information, and women who share health-related information on social media may be influenced by FT use, as the provision of personalized data and social network connectivity are key features of FT.[8,47–51]

Research indicates that FT is positively associated with communication behaviors on social media.[14] Many FTs offer features that allow users to share personal health data, such as weight or dietary habits, fostering communication and motivation among social media users.[49] Users frequently share personal health information to strengthen social connections and reinforce their motivation for healthy behaviors.[49,52,53] Additionally, FT, as a communication facilitator, may indirectly influence personal responses by prompting further communication. According to the Communication Mediation Model, communication shapes thoughts, emotions, and behaviors,[27] Shah, McLeod[26] revise this model by highlighting that communication fosters ongoing dialogue, leading to additional interactions. Building on this framework, FT users are likely to engage in more health-related discussions and seek complementary information across social platforms,[26,54,55] which may have both motivational and psychological effects.

While these interactions often reinforce positive health behaviors,[14,56,57] they can also contribute to anxiety and concern, particularly related to cancer.[23,24,58] Specifically, FT may heighten cancer worry indirectly through social media communication, such as sharing personal health data or seeking health information. For example, when users post early warning signs detected by FT, like unexplained weight loss, changes in menstrual cycles, or breast lumps,[59–62] their social media friends can comment, react,

and engage. These interactions not only foster discussion but also expose users to potentially alarming content related to cancer risks, prompting them to seek further health information.[27] Increased exposure to risk information has been linked to higher levels of cancer worry.[23,24,58] Given that women are generally more active on social media[11,21,63] and frequently seek cancer information,[64,65] thus, it is plausible that FT, by encouraging greater social media use, may contribute to higher levels of cancer worry among women.

Cancer worry, defined as persistent negative emotions related to cancer risk,[66] can drive preventive behaviors like cancer screening,[23,24,67] as when individuals aware of the dangers posed by cancer, people become increasingly concerned about their likelihood of developing it, which may motivate them to engage in preventive measures such as screening. Research consistently shows a positive correlation between communication factors and cancer screening behaviors via cancer worry among women.[23,24,68] For example, eHealth technologies that induce cancer worry have been shown to encourage women to undergo cervical cancer screenings.[24] Furthermore, studies by Jizhou Francis and Shenting Zheng suggest that patient-centered communication increases cancer worry, which in turn drives women to pursue breast and cervical cancer screenings.[68] Besides, drawing on social cognitive theory (SCT), which posits that behavior is influenced by reciprocal interactions between personal, environmental, and behavioral factors,[25] social media serves as a critical environmental factor that may shape perceptions of cancer risk and, consequently, motivate screening behaviors.

In summary, this study, grounded in the Communication Mediation Model and SCT, examines the potential for serial mediation between FT use, social media communication, and cancer worry in influencing cancer screening behaviors (see Figure 1). The Communication Mediation Model suggests that FT, as a digital tool, can facilitate increased communication on social media, which may in turn heighten cancer worry. SCT posits that social media, as an environmental factor, shapes perceptions of cancer risk, motivating preventive behaviors like cancer screening. Although numerous studies have independently explored the mediating roles of social media communication and cancer worry,[23,24] little is known about their role in the relationship between FT use and cancer screening behaviors, or how these factors interact over time. Thus, this study proposes five hypotheses:

H1: FT use will increase cancer screening behaviors.
H2: FT use will increase communication behaviors on social media.
H3: Communication behaviors on social media will increase cancer worry.
H4: Cancer worry will increase cancer screening behaviors.

H5: FT will impact cancer screening behaviors through the sequential mediation of increased social media communication and heightened cancer worry.

Method

Sampling

This study uses a quantitative research method based on HINTS data collected in the United States from 2017 to 2020. The data from these years were selected because the core variables were consistently measured during this period. Additionally, previous research on cancer screening among women has used this period as a reference.[24] HINTS is a nationally representative survey administered by the National Cancer Institute to assess American adults' access to health information, as well as their health-related knowledge, attitudes, and behaviors. More details about HINTS are available at https://hints.cancer.gov/. The total sample size across the four cycles was 15,408. After applying the final survey weights provided by HINTS, the weighted sample represented a total of 331,449,281 individuals. These final survey weights were used to ensure nationally representative estimates and were normalized across cycles to account for differences in sample sizes. Based on a dichotomous question about respondents' gender, this study included only individuals designated as female on their original birth certificates. To compare the overall changes in cancer screening behaviors over four years, we selecting women aged 18 and above, the final analytic sample consisted of 9245 women, representing 166,663,517 women in the U.S. population. In the pooled sample, these normalized weights were applied in all analyses to maintain proportional representation of the U.S. population. The final pooled sample size includes 1914 participants from HINTS 5 Cycle 1 (2017), 2054 from HINTS 5 Cycle 2 (2018), 3073 from HINTS 5 Cycle 3 (2019), and 2204 from HINTS 5 Cycle 4 (2020). To ensure the robustness of the findings, participants were divided into two groups based on USPSTF and ACOG screening guidelines to compare different types of cancer screening behaviors: the breast cancer screening group (women aged 40 and above) and the cervical cancer screening group (women aged 21 to 65).[69,70] The breast cancer screening group included 7249 participants, while the cervical cancer screening group included 6048 participants.

Measures

FT use was measured with two items, similar to prior research using the same data source.[14] Participants were asked if, in the past 12 months, they had (1) used a health or wellness app on a tablet or smartphone and (2) used an electronic wearable device (e.g., Fitbit, Apple Watch, or
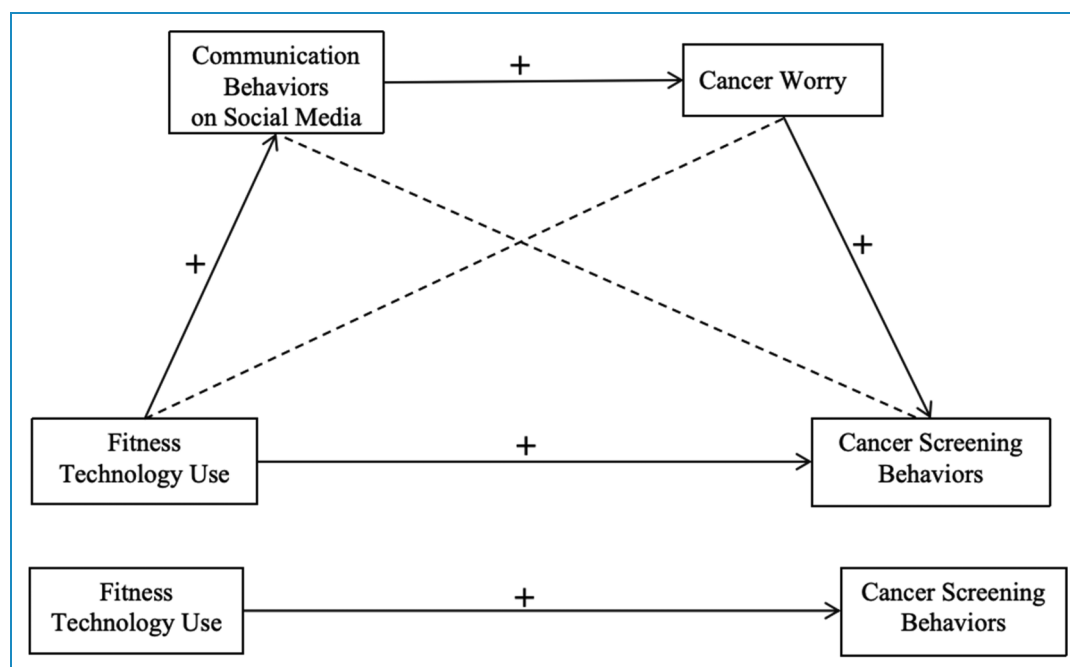
Figure 1. Conceptual framework of the sequential mediation model (consistent direction across 2017–2020).

Garmin Vivofit) to monitor health or activity. Responses were coded as "yes" (1) or "no" (0), and the two items were summed to create an additive measure of FT use, with higher scores indicating greater use. $M = 0.74/0.929/ 0.86/0.932$, SD $= 0.76/0.81/0.785/0.793$, corresponding to 2017, 2018, 2019, and 2020, respectively.

Communication behaviors on social media were measured using four items, adapted from national surveys using the same data source.[14,71] The question began with the statement: "Sometimes people use the Internet to connect with other people online through social networks like Facebook or Twitter; this is often called social media." Participants were then asked if, in the past 12 months, they had used the Internet for any of the following: (1) to visit a social networking site, such as Facebook or LinkedIn, (2) to share health information on social networking sites, such as Facebook or Twitter, (3) to participate in an online forum or support group for people with a similar health or medical issue, and (4) to watch a health-related video on YouTube. Respondents who answered "yes" to any of these categories were classified as using social media and defined as social media users. $M = 1.17/1.272/1.273/ 1.39$, $SD = 1.04/1.080/1.069/1.09$, corresponding to the years 2017, 2018, 2019, and 2020, respectively.

Cancer worry was operationalized with one single item, similar to previous research.[44] Respondents were asked to rate their cancer worry with the question "How worried are you about getting cancer?" A five-point scale was used (1 = not at all to 5 = extremely), where higher scores represented higher cancer worry. $M = 2.603/2.599/2.50/$ 2.84, $SD = 1.158/1.17/1.157/1.19$, corresponding to the years 2017, 2018, 2019, and 2020, respectively.

Cancer screening behaviors were measured using two items, similar to prior research.[24] Respondents were asked to report: (1) "How long ago did they have their most recent Pap test to check for cervical cancer?" (cervical cancer screening); and (2) "When did they have their most recent mammogram to check for breast cancer, if ever?" (breast cancer screening) (1 = never to 6 = a year ago or less). The six-point scale was chosen to balance simplicity and granularity. The choice of cutoff points "never" as "1" and "within the past year" as "6" was designed to capture the most recent screening behavior, which is highly relevant for understanding the timeliness of cancer screening. The two items were averaged to form a composite measure afterward, where higher scores indicate more timely and recent screening behaviors, reflecting a higher frequency of adherence to recommended screening schedules. We chose cervical/breast cancer screening as the focus of our study variable because these screening frequencies were consistently recorded across all waves of the HINTS data we analyzed. Given that both screening behaviors were measured using the same six-point scale and that previous studies,[23,24] using HINTS data have used the same composite score for these two screening behaviors, we selected the composite score for our analysis. The two screening behaviors are significantly correlated across years, $r = 0.197/0.220/0.213/ 0.157$, $p < .001/<.001/<.001/<.001$, $M = 4.59/4.39/4.43/ 4.35$, $SD = 1.37/1.44/1.43/1.42$, corresponding to the years 2017, 2018, 2019, and 2020, respectively.

Data analysis

SPSS version 25 was used for data analysis. Four types of analyses were conducted: (1) SPSS PROCESS (Model 6)[72] was used to examine the sequential mediating effects of communication behavior and cancer worry between FT use and general cancer screening behaviors. This model was chosen because it is well-suited for analyzing sequential mediation effects, where multiple mediators are tested in a specific order. Path coefficients were assessed using 10,000 bootstrap samples to obtain 95% bias-corrected CIs; (2) To ensure the robustness of the findings, Model 6 was then used separately to examine the sequential mediating effects of communication behavior and cancer worry between FT use and breast cancer screening behaviors, as well as cervical cancer screening behaviors. (3) one-way ANOVA with post hoc Games-Howell analysis to compare focal variables; and (4) year, treated as a continuous moderator, to examine changes over the years. Missing data were handled using listwise deletion.

Results

Descriptive statistics

Descriptive statistics for the independent, dependent, and control variables are presented in Table 1. In the weighted pooled sample, the average age was 50 years (SD = 17.90), and the mean household income was between $35,000 and $74,999 ($M$ = 5.50). Most participants had a college education or higher (62.2%), and nearly half (49.2%) were married or living as married. Additionally, nearly 30% of participants were single and had never been married (see Table 1 for more details). More information about the breast cancer screening group and the cervical cancer screening group is provided in Supplemental Table S1.

Mediation results

H1 predicted the positive relation between FT and cancer screening behaviors. As shown in Table 2, FT had a statistically significant relationship with cancer screening behaviors in 2018, 2019, and 2020 (b = 0.062/0.052/0.046, p < .01/<.01/<.05; respectively), providing partial support for H1.

H2 predicted that FT use would be positively associated with communication behaviors on social media, and this was supported by the results (b = 0.293/0.266/0.279/0.322, p < .001/.001/.001/.001; samples from 2017 to 2020, respectively).

H3 predicted the positive relation between communication behaviors on social media and cancer worry. Results partial support for H3 (b = 0.110/0.091/0.061, p < .001/<.001/<.05; samples from 2018, 2019, and 2020, respectively).

H4 predicted that cancer worry would be positively associated with cancer screening behaviors, and this was supported (b = 0.027/0.036/0.034/0.027, p < .05/<.01/<.01/<.01; samples from 2017 to 2020, respectively).

H5 posited that FT use would be positively associated with cancer screening behaviors through the sequential mediation of communication behaviors on social media and cancer worry. Results partially supported H5 (b = 0.001/0.001/0.001, 95% CI [0.0002, 0.002]/[0.0002, 0.002]/[0.0001, 0.001]; samples from 2018, 2019, and 2020, respectively). To ensure the robustness of the findings, two parallel analyses were conducted within the breast cancer screening group (women aged 40 and above) and the cervical cancer screening group (women aged 21 to 65), utilizing both four years of data and the total data over the four years. The results remained consistent in terms of the direction of coefficients and the statistical significance of the impact of FT on screening behaviors, as shown in Table 3 and Supplemental Table S2. To evaluate the influence of the year, we adhered to established textbook guidelines[73] and prior methodologies by aggregating data over four years and treating the year as a moderating variable.[74,75] The interaction term (year × FT) did not yield statistically significant results in predicting cervical cancer screening behavior (b = 0.009, p > .05), breast cancer screening behavior (b = 0.021, p > .05), and combined cancer screening behaviors (b = 0.006, p > .05) in the analysis using combined data from 2017 to 2020. This indicates that the relationship between FT use and cancer screening behaviors did not significantly change over time during the study period.

The trends of core variables

As shown in Figure 2 and Table 4, the results based on the weighted sample (ANOVA) showed a significant decrease in cancer screening behaviors from 2017 to 2020, with a mean difference of −0.26 (p < .001). In contrast, the unweighted annual mean values revealed a decrease from 4.59 in 2017 to 4.35 in 2020, indicating that, without weight adjustment, the results were consistent in direction. The level of FT use increased from 0.74 in 2017 to 0.93 in 2020, indicating a statistically significant increase (M_{diff} = 0.22, p < .001). The level of cancer worry increased from 2.60 in 2017 to 2.84 in 2020 (M_{diff} = 0.26, p < .001), with statistically significant differences observed every two years. Communication behaviors on social media increased from 1.17 in 2017 to 1.39 in 2020 (M_{diff} = 0.20, p < .001) with statistically significant differences observed every two years.

Table 1. Descriptive statistics of the independent, dependent, and controlled variables (2017–2020) (unweighted $N = 9245$; weighted $N = 166{,}663{,}517$).

Variable name	2017	2018	2019	2020	Pooled sample (unweighted)	Pooled sample (weighted)
Age	55.81 ± 16.51	55.90 ± 16.98	56.49 ± 17.24	56.53 ± 17.30	56.23 ± 17.05	50.00 ± 17.90
Education, n (%)						
Less than 8 years	32 (1.72%)	36 (1.77%)	47 (1.55%)	49 (2.29%)	164 (1.8%)	2,670,804 (1.6%)
8 through 11 years	97 (5.20%)	134 (6.60%)	162 (5.34%)	110 (5.14%)	503 (5.5%)	10,077,502 (6.1%)
12 years or completed high school	395 (21.18%)	377 (18.57%)	552 (18.21%)	436 (20.36%)	1760 (19.4%)	37,186,514 (22.7%)
Posthigh school training other than college	119 (6.38%)	127 (6.26%)	197 (6.50%)	139 (6.49%)	582 (6.4%)	12,206,256 (7.4%)
Some college	423 (22.68%)	480 (23.65%)	704 (23.23%)	461 (21.53%)	2068 (22.8%)	48,780,202 (29.7%)
College graduate	486 (26.06%)	536 (27.59%)	806 (26.59%)	560 (26.16%)	2388 (26.3%)	33,089,300 (20.2%)
Postgraduate	313 (16.78%)	340 (16.75%)	563 (18.57%)	386 (18.03%)	1602 (17.7%)	20,131,348 (12.3%)
Annual income (USD), n (%)						
0–9999	149 (8.72%)	147 (8.17%)	221 (8.11%)	162 (8.29%)	679 (8.3%)	12,245,741 (8.2%)
10,000–14,999	120 (7.02%)	116 (6.45%)	177 (6.49%)	125 (6.39%)	538 (6.6%)	8,052,086 (5.4%)
15,000–19,999	117 (6.85%)	107 (5.95%)	169 (6.20%)	113 (5.78%)	506 (6.2%)	7,911,249 (5.3%)
20,000–34,999	262 (15.33)	272 (15.12%)	394 (14.45%)	282 (14.42%)	1210 (14.8%)	19,103,826 (12.8%)
35,000–49,999	222 (12.99%)	239 (13.29%)	373 (13.68%)	266 (13.61%)	1100 (13.4%)	20,813,948 (13.9%)
50,000–74,999	295 (17.26%)	306 (17.01%)	487 (17.87%)	315 (16.11%)	1403 (17.1%)	25,590,808 (17.1%)
75,000–99,999	190 (11.12%)	212 (11.78%)	312 (11.45%)	224 (11.46%)	938 (11.5%)	19,246,732 (12.9%)
100,000–199,999	273 (15.97%)	297 (16.51%)	449 (16.47%)	350 (17.90%)	1369 (16.7%)	27,435,354 (18.3%)
200,000 or more	81 (4.74%)	103 (5.73%)	144 (5.28%)	118 (6.04%)	446 (5.4%)	9,213,143 (6.2%)
Marital status, n (%)						
Married	865 (46.78%)	839 (41.35%)	1260 (41.78%)	937 (43.74%)	3901 (43.2%)	80,411,184 (49.2%)

(continued)

Table 1. Continued.

Variable name	2017	2018	2019	2020	Pooled sample (unweighted)	Pooled sample (weighted)
Living as married or living with a romantic partner	52 (2.81%)	61 (3.01%)	160 (5.31%)	91 (4.25%)	364 (4.0%)	5,650,628 (3.5%)
Divorced	325 (17.58%)	380 (18.73%)	532 (17.64%)	380 (17.74%)	1617 (19.9%)	17,047,673 (10.4%)
Widowed	263 (14.22%)	319 (15.72%)	455 (15.09%)	311 (14.52%)	1348 (14.9%)	12,696,873 (7.8%)
Separated	47 (2.54%)	56 (2.76%)	76 (2.52%)	53 (2.47%)	232 (2.6%)	2,942,558 (1.8%)
Single, never been married	297 (16.06%)	374 (18.43%)	533 (17.67%)	370 (17.27%)	1574 (17.4%)	44,634,132 (27.3%)
Fitness technology usage in past 12 months	0.74 ± 0.76	0.929 ± 0.81	0.86 ± 0.79	0.932 ± 0.80	0.86 ± 0.79	0.89 ± 0.80
Cancer screening, Mean (SD)	4.59 ± 1.37	4.40 ± 1.44	4.43 ± 1.43	4.35 ± 1.42	4.44 ± 1.42	4.26 ± 1.55
Communication behaviors on social media, M (SD)	1.17 ± 1.04	1.272 ± 1.07	1.273 ± 1.07	1.39 ± 1.09	1.28 ± 1.07	1.39 ± 1.07
cancer worry, M (SD)	2.603 ± 1.16	2.599 ± 1.17	2.50 ± 1.16	2.84 ± 1.24	2.63 ± 1.19	2.70 ± 1.19

Note. SD stands for standard deviation.

Table 2. The effects of fitness technology use on cancer screening behaviors through social media communication and cancer worry each year.

Mediation pathways	Hypotheses	2017 B	95% CI	2018 b	95% CI	2019 b	95% CI	2020 b	95% CI
Total effect									
Fitness technology use → cancer screening behaviors		0.032	[−0.059, 0.123].	0.073***	[0.036, 0.100]	0.0526**	[0.020, 0.086]	0.0534**	[0.018, 0.089]
Direct effect									
Fitness technology use → communication behaviors on social media	H2	0.293***	[0.230, 0.356]	0.266***	[0.204, 0.329]	0.279***	[0.233, 0.335]	0.322***	[0.260, 0.385]
Fitness technology use → cancer worry		0.045	[−0.035, 0.124]	0.081*	[0.004, 0.158]	−0.019	[−0.088, 0.050]	0.028	[−0.054, 0.110]
Communication behaviors on social media → cancer worry	H3	0.019	[−0.042, 0.080]	0.110***	[0.047, 0.173]	0.091***	[0.040, 0.141]	0.061*	[0.003,0.119]
Communication behaviors on social media → cancer screening behaviors		0.007	[−0.021, 0.035]	0.023	[−0.007, 0.054]	0.003	[−0.022, 0.028]	0.019	[−0.007, 0.045]
Cancer worry → cancer screening behaviors	H4	0.027*	[0.004, 0.035]	0.036**	[0.011, 0.061]	0.034**	[0.013, 0.054]	0.027**	[0.007, 0.048]
Fitness technology use → cancer screening behaviors	H1	0.013	[−0.024, 0.049]	0.062**	[0.025, 0.100]	0.0515**	[0.018, 0.085]	0.046*	[0.010, 0.082]
Indirect effect									
Fitness technology use → communication on social media → cancer screening behaviors		0.003	[−0.008, 0.014]	0.006	[−0.002, 0.014]	0.001	[−0.006, 0.008]	0.006	[−0.002, 0.015]
Fitness technology use → cancer worry → cancer screening behaviors		0.002	[−0.001, 0.006]	0.003	[0.0001, 0.007]	−0.001	[−0.003, 0.002]	0.001	[−0.002, 0.004]
Fitness technology use → communication behaviors on social media → cancer worry → cancer screening behaviors	H5	0.0002	[−0.005, 0.001]	0.001	[0.0002, 0.002]	0.001	[0.0002, 0.002]	0.001	[0.0001, 0.001]

Note. Unstandardized betas are shown in each cell; * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 3. Summary of different path effects in two types of cancer screening behaviors each year.

Mediation Pathways	2017		2018		2019		2020	
	B	95% CI	b	95% CI	b	95% CI	B	95% CI
DV: Cervical cancer screening (N = 6048)								
Fitness technology → communication behaviors on social media	0.271***	[0.194, 0.348]	0.297***	[0.218, 0.374]	0.217***	[0.148, 0.286]	0.331***	[0.253, 0.409]
Communications behavior on social media → cancer worry	0.001	[−0.068, 0.070]	0.120**	[0.046, 0.194]	0.075*	[0.016, 0.134]	0.073	[−0.071, 0.124]
Cancer worry → cancer screening	0.039	[−0.029, 0.107]	0.064	[−0.015, 0.143]	0.084*	[0.020, 0.148]	0.001	[−0.071, 0.070]
Fitness technology → communication behaviors on social media → cancer worry → cancer screening	0.0001	[−0.001, 0.001]	0.002	[−0.001, 0.006]	0.001	[0.0001, 0.003]	0.0001	[−0.002, 0.002]
Direct effect: Fitness technology → cancer screening	0.010	[−0.097, 0.117]	0.163**	[0.044, 0.282]	0.176***	[0.076, 0.277]	0.064	[−0.055, 0.184]
DV: breast cancer screening (N = 7249)								
Fitness technology → communication behaviors on social media	0.318***	[0.247, 0.389]	0.300***	[0.222, 0.378]	0.313***	[0.242, 0.385]	0.282***	[0.206, 0.358]
Communication behaviors on social media → cancer worry	0.011	[−0.059, 0.079]	0.097*	[0.015, 0.179]	0.099**	[0.037, 0.162]	0.010	[−0.060, 0.079]
Cancer worry → cancer screening	0.100**	[0.030, 0.169]	0.118*	[0.026, 0.209]	0.101**	[0.029, 0.174]	0.126***	[0.058, 0.194]
Fitness technology → communication behaviors on social media → cancer worry → cancer screening	0.0004	[−0.002, 0.003]	0.003	[0.0002, 0.008]	0.003	[0.001, 0.007]	0.0003	[−0.002, 0.003]
Direct effect: Fitness technology → cancer screening	0.047	[−0.066, 0.159]	0.222**	[0.087, 0.356]	0.273***	[0.158, 0.387]	0.212***	[0.095, 0.328]

Note. DV: dependent variable; CI: confidence interval.
All models control for age, household income, education, and marital status.
*p < .05; **p < .01; ***p < .001.
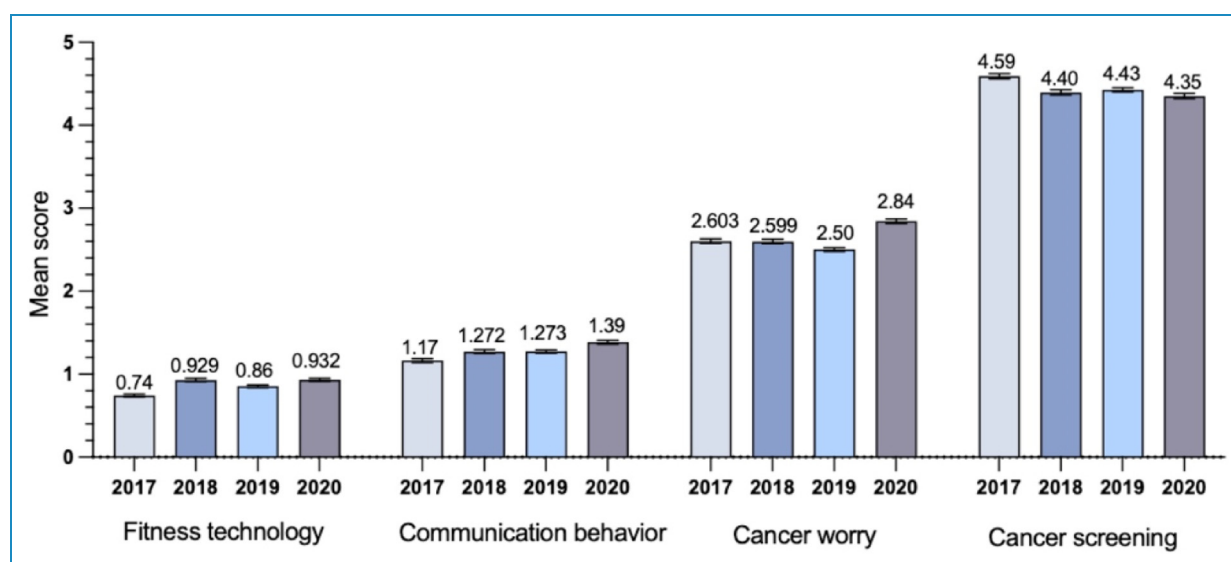
Figure 2. The comparison of combined cancer screening behaviors, fitness technology, communication behavior and cancer worry.

Table 4. Multiple comparisons of the cancer screening, fitness technology, communication behavior, and cancer worry (weighted).

Variable name	Year 2020 versus 2019	Year 2020 versus 2018	Year 2020 versus 2017
Cancer screening	−0.133***	−0.166***	−0.257***
Fitness technology	0.061***	0.031***	0.213***
Communication behavior on social media	0.049***	0.097***	0.202***
Cancer worry	0.320***	0.283***	0.261***

Notes. The main cell is the difference in mean; one-way ANOVA analysis with post hoc analysis (Games-Howell method) was used.
***$p < .001$.

Discussion

This trend analysis study explored the influence of FT use on cancer screening behaviors among American women, investigating whether increased use of such technology promotes greater engagement in social media communication and heightens cancer worry, ultimately leading to higher rates of cancer screenings. The study drew on four recent cycles (2017–2020) of nationally representative data from the HINTS survey.

Analysis of the trends of core variables

First, our findings reveal an upward trend in cancer screening behaviors from 2018 to 2019, following declines from 2017 to 2018 and from 2019 to 2020. The increase during this period could potentially be related to social media platforms spreading health information and promoting public health campaigns.[47,76] Additionally, the growing adoption of smartphones and the increasing accessibility of more user-friendly wearable devices became particularly influential from 2018 onward.[77,78] By this time, wearable devices were more advanced, offering features such as heart rate monitoring, sleep tracking, and personalized health insights, which likely made them more useful and appealing for individuals focused on health management.[79] These technological shifts might have contributed to making fitness tracking and health-related information more accessible and appealing,[79] possibly influencing interest in preventive health behaviors, such as cancer screening. Health literacy may also be important in this context, as individuals with higher health literacy are more likely to engage with these technologies and health information effectively,[80] which potentially leads to increased cancer screening behaviors. Moreover, access to healthcare may play a significant role in enabling individuals to act on health information. Those with better access to healthcare services may be more likely to participate in screening programs, while those with limited access may face barriers despite the technological advancement.[81]

The decline from 2017 to 2018 could be attributed to changes in healthcare policies and economic factors, as individuals facing reduced financial security may be less likely to prioritize preventive health measures.[82,83] Additionally, regional differences in healthcare access and infrastructure might have contributed to varying levels of cancer screening participation. For instance, individuals in rural areas or regions with fewer healthcare resources may have experienced greater challenges in accessing screening

services.[84] The drop in screening behaviors from 2019 to 2020 could potentially be influenced by the COVID-19 pandemic, which disrupted healthcare services and led to the postponement or cancelation of many screening programs.[85] Specifically, during the COVID-19 pandemic, healthcare resource strain and restrictions on nonessential procedures likely caused delays in cancer screenings for some individuals.[86] This impact may have been felt more by those using health monitoring technologies, like wearable devices, which, while helpful, cannot replace medical screenings. Although these technologies may have increased health awareness, actual screening behaviors were still influenced by healthcare access and policy restrictions. A study found that, compared to previous years, breast screenings in the United States. decreased by 87% and cervical screenings by 84% in April 2020.[87] This underscores the potential effect of healthcare disruptions on essential services, including cancer screenings. Second, the increased use of FT may be attributed to the advancements in its design and functionality,[88] making it more appealing and accessible to a broader audience. Third, communication behaviors on social media exhibited a steady year-over-year increase from 2017 to 2020. The potential reason could be the widespread adoption of smartphones and internet access,[21] which made social media more accessible, while the rise of visual and interactive content, such as videos and live streaming, enhanced user engagement. Finally, there was an overall increase in cancer worry from 2017 to 2020. possibly due to persistently high mortality rates associated with breast and cervical cancer in the United States.[89–91]

Mediation analysis

As anticipated, this study identified the sequential mediating role of communication behaviors on social media and cancer worry in the relationship between FT use and cancer screening behaviors. FT use was positively associated with communication behaviors on social media, which, in turn, positively linked to cancer worry and subsequently to cancer screening behaviors.

H1 predicted a positive relationship between FT and cancer screening behaviors in 2018, 2019, and 2020. The *p*-values indicate that these relationships are statistically significant, suggesting that the use of FT is potentially reliably associated with increased cancer screening behaviors among women during these years. The association between FT use and cancer screening behaviors in 2017 was nonsignificant, which may reflect the early stage of adoption of FT at that time,[92] and users have limited ability to operate FT during that period.[93] While fitness apps and wearable devices were gaining popularity, their usage was not yet widespread or consistent.[92] Many individuals were hesitant to adopt these technologies due to concerns over their usability, accuracy, and effectiveness,[42,94] which could

have limited their integration into daily health behaviors like cancer screening. Additionally, early-stage fitness technologies primarily focused on tracking physical activity rather than comprehensive health-related behaviors, such as cancer prevention and screening.[42] This limited functionality may have hindered users from perceiving FT as a tool for promoting cancer screening. The relatively low adoption rate, combined with the early-stage nature of the technologies, likely explains why a significant relationship between FT and cancer screening behaviors was not observed in 2017. Furthermore, the findings revealed a diminishing trend in the direct effect of FT on both cervical and breast cancer screening. This may be due to the advancements in cancer screening options. For instance, cervical cancer screening has transitioned from the traditional Pap test to more sensitive methods like HPV testing and co-testing.[95,96] These newer options provide more accurate results and longer intervals between screenings,[97] reducing the necessity for regular reminders delivered through fitness technologies. Similarly, Improved breast cancer screening methods, such as digital mammography, have contributed to more accurate and efficient detection of early-stage cancers, reducing false positives and unnecessary follow-up tests,[98] this may increase patient confidence in screening results, lessening the perceived need for additional reminders or health monitoring.

As predicted by hypotheses H2, H3, and H4, this study identified a significant sequential mediation model. The use of FT positively influences cancer screening behaviors through its impact on communication behaviors via social media and cancer worry. The findings are consistent with existing research that suggests technological affordances may play a role in influencing behavioral changes.[48,50,88] For example, Zheng and Li[14] demonstrate that applications and trackers equipped with features that promote sharing personal health information and viewing supplementary health-related videos facilitate behavioral changes. Moreover, the cost-effectiveness and ease of integrating FT with social media platforms may enhance user engagement.[99,100] Specifically, the *p*-values for each year (all < .001) suggest that the relationship between FT use and communication behaviors on social media is statistically significant across all four years, indicating that this effect is unlikely to be random. Additionally, the CIs for each year, ranging from [0.230, 0.356] in 2017 to [0.260, 0.385] in 2020, show that the impact of FT remained positive. The growing effect size over time may reflect the increasing integration of FT into daily life, which could have encouraged more frequent health-related discussions online. The widening CIs also suggest a potential strengthening of this relationship over time, possibly due to greater user engagement and a growing focus on health-related content.[26]

The findings align with the Communication Mediation Model,[26] indicating that FT, as a digital tool directly may

enhance communication behavior on social media. As users engage with FT, they are more likely to share and seek health experiences and information,[24] which may foster discussions about health topics such as cancer and connecting with communities facing similar health challenges. While these interactions can promote awareness and knowledge,[101] they also expose users to health information and risk-related content, heightening their awareness of potential health threats[102] and intensifying anxiety about health risks.[103] Consequently, it is plausible that this exposure to social media increases cancer worry. Furthermore, the p-values for 2018–2010 (all <.05) suggest that the relationship between communication behaviors on social media and cancer worry was statistically significant and unlikely to be due to random chance. However, it is noteworthy that the positive influence of communication behaviors on social media on cancer worry has decreased over the years, particularly by 2020. The CIs for 2018 ([0.047, 0.173]) show a relatively strong effect, with the lower bound still indicating a meaningful relationship. However, in 2020, the interval ([0.003, 0.119]) narrowed and moved closer to zero, suggesting a weaker effect and potentially indicating a shift in how individuals engage with cancer-related content on social media. This decreasing trend may be attributed to the increasing volume of health-related content on social media, which, over time, may overwhelm users.[104] The proliferation of both credible and misleading information could lead to "information fatigue," making it increasingly difficult for users to distinguish reliable sources from misinformation.[105] Over time, individuals may have become desensitized to the constant flow of health-related information,[106,107] further weakening its impact on cancer-related concern.[108,109] As a result, the effectiveness of social media as a health communication tool diminishes, thereby reducing its impact on cancer worry and potentially lessening its influence on cancer screening behaviors.

As suggested by SCT, social environmental factors can influence personal factors, thereby shaping behavior.[25] Social media platforms serve as an external factor for users to share and seek health information, exposing them to risk-related content that increases awareness of health threats like cancer.[102] This heightened awareness can lead to increased worry about cancer risk, motivating individuals to engage in preventive behaviors such as screening.[23,24,67] Cancer worry, often prompted by communication factors, can directly enhance cancer screening behaviors among women, consistent with previous research findings.[23,24] For instance, studies show that anxiety related to cancer, spurred by eHealth technologies, can encourage women to participate in cervical cancer screening.[24] Similarly, research by Jizhou Francis and Shenting Zheng demonstrates that patient-centered communication can elevate cancer worry among women, prompting them to undergo screenings for both breast and cervical cancer.[23] Moreover, our findings reveal that the direct positive effect of cancer worry on cancer screening behavior diminished each year from 2018 to 2020. This trend may be attributed to the advancements in screening technologies in recent years, such as the introduction of HPV testing, which allowed for longer screening intervals,[95–98] reducing immediate concerns.

In conclusion, this study demonstrates that FT is positively correlated with cancer screening behavior through the sequential mediation of communication behaviors on social media and cancer worry. While the magnitude of the pathway effects fluctuated over time, the overall sequential mediation effect remained relatively stable. The directional relationships between variables in the model were consistent and not significantly impacted by temporal changes. However, it is important to note that, given the repeated cross-sectional design of this study, the findings indicate correlations rather than causal relationships. The observed trends may be influenced by multiple factors, and future longitudinal or panel studies would help confirm the directionality of these effects.

Supplementary analysis

As indicated in Supplemental Table S1, the mean score of FT use is lower in the breast cancer screening group ($M = 0.800$) compared to the cervical cancer screening group ($M = 0.955$). However, as shown in Supplemental Table S2, both the direct and sequential indirect effects of FT on cancer screening over the four years appear to be stronger in the breast cancer screening group than in the cervical cancer screening group. Additionally, as shown in Table 3, the mediating effect of FT on breast cancer screening became significant in 2018, while its effect on cervical cancer screening seemed to emerge a year later. This disparity could potentially be influenced by the earlier promotion and public awareness of breast cancer in the United States compared to cervical cancer. For instance, the American Cancer Society advocated for breast self-examinations[110] earlier than for routine cervical cytology screening.[111] Thus, the public might have more health knowledge and health literacy related to breast cancer than cervical cancer. One study suggests that public knowledge about breast cancer tends to surpass that of cervical cancer.[112] Based on the reasoning from the "mediation analysis," this difference in awareness may have contributed to a greater focus on breast cancer screening as FT gained popularity, which could have led to more communication on this topic through social media and potentially heightened cancer worry, thereby possibly influencing screening behaviors for breast cancer more than for cervical cancer. Public health departments could consider leveraging fitness technologies, such as health apps and wearable devices, to enhance breast cancer screening participation. They may incorporate personalized health reminders and data monitoring to optimize outreach strategies.

For cervical cancer screening, however, the relatively weaker impact of FT may suggest a need for further alignment between the technology design and the specific data monitoring needs of cervical cancer prevention. Policymakers may need to explore additional strategies, such as strengthening educational campaigns to improve health literacy around cervical cancer and enhancing the accessibility of screenings, to address the relatively limited influence of technology and increase engagement in preventive behaviors. However, it is important to note that these findings suggest correlations rather than causal relationships. The observed trends could be influenced by multiple factors, and further longitudinal or panel studies are needed to confirm the directionality of these effects. These findings highlight the potential of FT as a tool for promoting both breast and cervical cancer screening, but further research is required to explore its role in health interventions.

Theoretical and practical implications

This study contributes to the growing body of research linking FT use with health behavior change by integrating the Communication Mediation Model and SCT into a sequential mediating model. Through the lens of CMM, the findings demonstrate how FT use drives communication behaviors on social media, illustrating how external digital tools influence the sharing of health-related information. This establishes the first step in the sequential mediation, where FT use indirectly affects health behavior through its influence on communication. Building on this, SCT explains the subsequent steps in the mediation, where social media communication enhances cancer worry, and cancer worry then motivates women to engage in cancer screening behaviors. This aligns with SCT's focus on how personal perceptions, shaped by external communication, lead to behavior change. This dual-theoretical framework contributes significantly to the theoretical understanding of how digital health interventions can influence preventive health behaviors among woman. Future digital health interventions targeting women's health can utilize this dual-theoretical framework to design strategies. For example, CMM can be used to create and strengthen online communities where women share experiences and health information. Meanwhile, SCT can be integrated to promote social learning and peer influence, enhancing women's cancer worry and transforming it into a constructive force that motivates cancer screening behaviors. By combining these theoretical insights, interventions can not only effectively communicate health information but also better engage and motivate women, ultimately improving the overall effectiveness of preventive health programs. Overall, the sequential mediation model highlights how FT shapes cancer screening behaviors by first fostering online health communication and then influencing personal psychological factors such as cancer worry, particularly in the context of cancer prevention among women. By integrating these two theoretical perspectives, this study provides a comprehensive framework for understanding how digital health tools influence preventive health behaviors through a layered process.

Practically, the results highlight the potential for integrating fitness technologies with social media platforms to enhance public health interventions, especially for women. Healthcare providers and policymakers can incorporate tools like health-tracking apps, personalized notifications, and online peer support groups within fitness technologies to drive cancer prevention behaviors. For example, mobile fitness apps could be used to send personalized cancer screening reminders or host virtual support groups where women can share their experiences and health concerns. These activities may help appropriately increase cancer-related worry, thereby further motivating women to engage in cancer screening. Given the consistent impact of communication behaviors and cancer worry on screening, tailored interventions that combine FT with educational content on social media can further motivate women to participate in regular cancer screenings. Moreover, as digital health tools and platforms continue to evolve, interventions must remain adaptive, incorporating emerging technologies. For example, new features such as AI-driven chatbots could be integrated into fitness apps to offer personalized, real-time health advice and reminders, helping to keep users engaged and informed. Expanding telehealth capabilities within fitness technologies could also provide women with access to remote consultations, further offering psychological incentives for cancer screening behaviors. This adaptability ensures that public health initiatives stay relevant and effective in promoting proactive health management and cancer prevention. Additionally, given the waning effect of social media communication on cancer worry over time, it is crucial that future interventions move beyond simply increasing content volume. Instead, they should incorporate nuanced communication strategies, such as targeted messaging and credible sources, to maintain engagement and effectiveness in addressing cancer-related concerns.

Finally, it is worth noting that while this study demonstrates statistically significant sequential mediation effects over three years, the small effect sizes suggest that FT may not be an independent driver of cancer screening behaviors. In other words, the impact of FT may be more significant when integrated with broader public health strategies. Other factors, such as health literacy, socioeconomic status, and social support, should also be considered when using FT to promote health behaviors, previous research has shown that these factors can facilitate the positive effects of health technology on health behaviors.[113–115] For instance, one study found that individuals with higher health literacy are more likely to use health technology to engage in health behaviors.[116] In real-world settings, FT could complement other interventions aimed at increasing

cancer screening rates, such as health education campaigns or improvements in healthcare accessibility. Future research should explore how FT can work in conjunction with other health promotion initiatives, such as educational programs or policy interventions, to create more comprehensive cancer screening strategies.

Limitations and future directions

This study has several limitations. First, the use of self-reported data may introduce recall bias, as participants might inaccurately report their technology usage or cancer screening behaviors. Self-reports are susceptible to various biases, including forgetfulness and social desirability bias. Future research could utilize objective data from fitness apps or wearable devices, such as device-tracked physical activity and cancer screening reminders, to validate participants' self-reported behaviors, thereby enhancing accuracy. Secondly, given the repeated cross-sectional design, it cannot establish causal relationships between FT use, social media communication, cancer worry, and screening behaviors. To address this issue, future research could use longitudinal or panel data to track individual changes over time. This approach would provide a clearer understanding of how changes in FT use influence cancer screening behaviors. Longitudinal data can also control for individual-level confounders, helping to clarify the directionality of causal relationships. The third limitation of this study is the comprehensiveness of cancer screening. For instance, colorectal cancer screening was not included because the 2017 HINTS dataset only covered individuals with a history of cancer and did not represent the general female population. Given the significance of colorectal cancer in women's health, future studies should incorporate additional cancer screening programs to provide a more comprehensive understanding of cancer screening behaviors among women. Finally, emerging digital health technologies, such as AI-driven interventions, have the potential to overcome some of the limitations identified in this study. For example, AI-powered tools could analyze users' behavior in real-time and deliver more personalized interventions that adapt to users' specific health needs. These technologies could also provide more accurate tracking of health behaviors, reducing reliance on self-reports, and improve the accessibility and effectiveness of health interventions. Future research could explore how such technologies might enhance engagement with cancer screening behaviors, particularly in underserved populations, by offering more targeted and timely health communication.

Conclusion

This study demonstrates that FT positively influences cancer screening behaviors through communication on social media and cancer worry. While the effects fluctuated over time, the overall mediation remained stable. Future interventions should focus on nuanced communication strategies, like targeted messaging and credible sources, and incorporate emerging technologies such as AI-driven chatbots and telehealth to enhance engagement and effectively address cancer-related concerns.

ORCID iDs

Yingxia Zhu https://orcid.org/0009-0005-5383-6420
Qingqing Xie https://orcid.org/0000-0002-7497-0339

Supplemental material

Supplemental material for this article is available online.

References

1. National Cancer Institute. *Cancer stat facts: cervical cancer*. Bethesda, MD, USA: National Cancer Institute, 2024; (accessed 24 November 2024).

2. American Cancer Society. *Key statistics for breast cancer*. Amerian Cancer Society, 2024 (accessed 24 November 2024).

3. Bender JL, Yue RYK, To MJ, et al. A lot of action, but not in the right direction: systematic review and content analysis of smartphone applications for the prevention, detection, and management of cancer. *J Med Internet Res* 2013; 15: e2661.

4. Sangers T, Wakkee M, Kramer-Noels E, et al. Views on mobile health apps for skin cancer screening in the general population: an in-depth qualitative exploration of perceived barriers and facilitators. *Br J Dermatol* 2021; 185: 961–969.

5. Lynch BM, Nguyen NH, Moore MM, et al. A randomized controlled trial of a wearable technology-based intervention for increasing moderate to vigorous physical activity and reducing sedentary behavior in breast cancer survivors: the ACTIVATE trial. *Cancer* 2019; 125: 2846–2855.

6. Loncar-Turukalo T, Zdravevski E, da Silva JM, et al. Literature on wearable technology for connected health: scoping review of research trends, advances, and barriers. *J Med Internet Res* 2019; 21: e14017.

7. Cadmus-Bertram LA, Marcus BH, Patterson RE, et al. Randomized trial of a Fitbit-based physical activity intervention for women. *Am J Prev Med* 2015; 49: 414–418.

8. Higgins JP. Smartphone applications for patients' health and fitness. *Am J Med* 2016; 129: 11–19.

9. Rising CJ, Jensen RE, Moser RP, et al. Characterizing the US population by patterns of mobile health use for health and behavioral tracking: analysis of the national cancer institute's health information national trends survey data. *J Med Internet Res* 2020; 22: e16299.

10. Damberg S. Predicting future use intention of fitness apps among fitness app users in the United Kingdom: the role of health consciousness. *Int J Sports Marketing and Sponsorship* 2022; 23: 369–384.

11. Montagni I, Cariou T, Feuillet T, et al. Exploring digital health use and opinions of university students: field survey study. *JMIR Mhealth Uhealth* 2018; 6: e9131.

12. Raman P and Aashish K. Gym users: an enabler in creating an acceptance of sports and fitness wearable devices in India. *Int J Sports Marketing and Sponsorship* 2022; 23: 707–726.

13. Wei J, Vinnikova A, Lu L, et al. Understanding and predicting the adoption of fitness mobile apps: evidence from China. *Health Commun* 2021; 36: 950–961.

14. Zheng X and Li W. Association between fitness technology use and physical activity mediated by communication behaviors on social media. *Digital Health* 2024; 10: 1–10.

15. Gal R, May AM, van Overmeeren EJ, et al. The effect of physical activity interventions comprising wearables and smartphone applications on physical activity: a systematic review and meta-analysis. *Sports Medicine-Open* 2018; 4: 1–15.

16. Case MA, Burwick HA, Volpp KG, et al. Accuracy of smartphone applications and wearable devices for tracking physical activity data. *Jama* 2015; 313: 625–626.

17. China Daily. *Fitness apps have more than 100 million users, with women accounting for more than 60%*. Beijing, China: China Daily, 2018.

18. Pew Research Center. About one-in-five Americans use a smart watch or fitness tracker. 2020, https://www.pewresearch.org/short-reads/2020/01/09/about-one-in-five-americans-use-a-smart-watch-or-fitness-tracker/ (accessed 20 December 2024).

19. Xie Z, Nacioglu A and Or C. Prevalence, demographic correlates, and perceived impacts of mobile health app use amongst Chinese adults: cross-sectional survey study. *JMIR Mhealth Uhealth* 2018; 6: e9002.

20. Carroll JK, Moorhead A, Bond R, et al. Who uses mobile phone health apps and does use matter? A secondary data analytics approach. *J Med Internet Res* 2017; 19: e125.

21. Pew Research Center. Americans' social media use. 2024, https://www.pewresearch.org/internet/2024/01/31/americans-social-media-use/ (accessed January 31 2024).

22. Epstein RM and Street RL. The values and value of patient-centered care. *Annals Family Med* 2011; 9(2): 100–103.

23. Ye JF, Zheng S, Ao SH, et al. How does patient-centered communication work? Trend analysis of mediation through cancer worry and health self-efficacy, 2011–2020. *J Health Psychol* 2024; 29(10): 1–15.

24. Liu PL, Ye JF, Ao HS, et al. Effects of electronic personal health information technology on American women's cancer screening behaviors mediated through cancer worry: Differences and similarities between 2017 and 2020. *Digital Health* 2023; 9: 1–12.

25. Bandura A. Social foundations of thought and action: a social cognitive theory. *Englewood Cliffs, NJ* 1986; 1986: 2.

26. Shah DV, McLeod DM, Rojas H, et al. Revising the communication mediation model for a new political communication ecology. *Hum Commun Res* 2017; 43: 491–504.

27. West RL, Turner LH and Zhao G. *Introducing communication theory: analysis and application*. New York, NY: McGraw-Hill, 2010.

28. Sullivan AN and Lachman ME. Behavior change with fitness technology in sedentary adults: a review of the evidence for increasing physical activity. *Front Public Health* 2017; 4: 289.

29. Moglia ML, Nguyen HV, Chyjek K, et al. Evaluation of smartphone menstrual cycle tracking applications using an adapted applications scoring system. *Obstet Gynecol* 2016; 127: 1153–1160.

30. Lupton D and Maslen S. How women use digital technologies for health: qualitative interview and focus group study. *J Med Internet Res* 2019; 21: e11481.

31. WHO. *Cancer control: knowledge into action: WHO guide for effective programmes*. Geneva, Switzerland: World Health Organization, 2007.

32. Valcarce-Torrente M, Javaloyes V, Gallardo L, et al. Influence of fitness apps on sports habits, satisfaction, and intentions to stay in fitness center users: an experimental study. *Int J Environ Res Public Health* 2021; 18: 10393.

33. Duffy SW, Tabár L, Yen AM-F, et al. Beneficial effect of consecutive screening mammography examinations on mortality from breast cancer: a prospective study. *Radiology* 2021; 299: 541–547.

34. İz FB and Tümer A. Assessment of breast cancer risk and belief in breast cancer screening among the primary health-care nurses. *J Cancer Educ* 2016; 31: 575–581.

35. Ardahan M, Dinc H, Yaman A, et al. Health beliefs of nursing faculty students about breast cancer and self breast examination. *Asian Pac J Cancer Prev* 2015; 16: 7731–7736.

36. Landy R, Pesola F, Castañón A, et al. Impact of cervical screening on cervical cancer mortality: estimation using stage-specific results from a nested case–control study. *Br J Cancer* 2016; 115: 1140–1146.

37. Broeders M, Moss S, Nyström L, et al. The impact of mammographic screening on breast cancer mortality in Europe: a review of observational studies. *J Med Screen* 2012; 19: 14–25.

38. Humphrey LL, Helfand M, Chan BK, et al. Breast cancer screening: a summary of the evidence for the US preventive services task force. *Ann Intern Med* 2002; 137: 347–360.

39. Winters S, Martin C, Murphy D, et al. Breast cancer epidemiology, prevention, and screening. *Prog Mol Biol Transl Sci* 2017; 151: 1–32.

40. Musa J, Achenbach CJ, O'Dwyer LC, et al. Effect of cervical cancer education and provider recommendation for screening on screening rates: a systematic review and meta-analysis. *PLoS One* 2017; 12: e0183924.

41. Aitken M and Nass D. *Digital health trends 2021: innovation, evidence, regulation, and adoption*. IQVIA Institute for Human Data Science, 2021

42. Piwek L, Ellis DA, Andrews S, et al. The rise of consumer health wearables: promises and barriers. *PLoS Med* 2016; 13: e1001953.

43. McCarroll ML, Armbruster S, Pohle-Krauza RJ, et al. Feasibility of a lifestyle intervention for overweight/obese endometrial and breast cancer survivors using an interactive mobile application. *Gynecol Oncol* 2015; 137: 508–515.

44. Allen CG, McBride CM, Haardörfer R, et al. Associations between objective television exposure and cancer perceptions in a national sample of adults. *Cancer Control* 2019; 26: 1–9.

45. Low CA. Harnessing consumer smartphone and wearable sensors for clinical cancer research. *NPJ Digit Med* 2020; 3: 140.

46. Leist AK. Social media use of older adults: a mini-review. *Gerontology* 2013; 59: 378–384.

47. Park HG, Kim Y-I, Huh WK, et al. The association between social media use for health related information and compliance with breast and cervical cancer screenings. *Res Rep (Montgomery)* 2020; 4: e1.

48. Zhu Y, Dailey SL, Kreitzberg D, et al. "Social networkout": connecting social features of wearable fitness trackers with physical exercise. *J Health Commun* 2017; 22: 974–980.

49. Lomborg S and Frandsen K. Self-tracking as communication. *Inf Commun Soc* 2016; 19: 1015–1027.

50. Molina MD and Sundar SS. Can mobile apps motivate fitness tracking? A study of technological affordances and workout behaviors. *Health Commun* 2020; 35(1): 65–74.

51. Whelan E and Clohessy T. How the social dimension of fitness apps can enhance and undermine wellbeing: a dual model of passion perspective. *Inf Technol People* 2021; 34: 68–92.

52. Lupton D. Lively data, social fitness and biovalue: the intersections of health and fitness self-tracking and social media. In *The sage handbook of social media*. Thousand Oaks, CA: Sage Publications, 2018; 562–578.

53. Lupton D. "Sharing is caring:" Australian self-trackers' concepts and practices of personal data sharing and privacy. *Front Digit Health* 2021; 3: 649275.

54. Li W, Watts J and Tan N. From screen to screening: entertainment and news television media effects on cancer screening behaviors. *J Health Commun* 2019; 24: 385–394.

55. Holbert RL. Intramedia mediation: the cumulative and complementary effects of news media use. *Pol Commun* 2005; 22: 447–461.

56. Korda H and Itani Z. Harnessing social media for health promotion and behavior change. *Health Promot Pract* 2013; 14: 15–23.

57. Rus HM and Cameron LD. Health communication in social media: message features predicting user engagement on diabetes-related Facebook pages. *Ann Behav Med* 2016; 50: 678–689.

58. Chae J. Online cancer information seeking increases cancer worry. *Comput Human Behav* 2015; 52: 144–150.

59. Ray PP, Dash D and De D. A systematic review of wearable systems for cancer detection: current state and challenges. *J Med Syst* 2017; 41: 1–12.

60. Holly EA, Chaliha I, Bracci PM, et al. Signs and symptoms of pancreatic cancer: a population-based case-control study in the San Francisco Bay area. *Clin Gastroenterol Hepatol* 2004; 2: 510–517.

61. Haynes BP, Ginsburg O, Gao Q, et al. Menstrual cycle associated changes in hormone-related gene expression in oestrogen receptor positive breast cancer. *NPJ Breast Cancer* 2019; 5: 42.

62. Barlow WE, Lehman CD, Zheng Y, et al. Performance of diagnostic mammography for women with signs or symptoms of breast cancer. *J Natl Cancer Inst* 2002; 94: 1151–1159.

63. Bidmon S and Terlutter R. Gender differences in searching for health information on the internet and the virtual patient-physician relationship in Germany: exploratory results on how men and women differ and why. *J Med Internet Res* 2015; 17: e156.

64. Vilhauer RP. Perceived benefits of online support groups for women with metastatic breast cancer. *Women Health* 2009; 49: 381–404.

65. Unruh HK, Bowen DJ, Meischke H, et al. Women's approaches to the use of new technology for cancer risk information. *Women Health* 2004; 40: 59–78.

66. Jensen JD, Bernat JK, Davis LA, et al. Dispositional cancer worry: convergent, divergent, and predictive validity of existing scales. *J Psychosoc Oncol* 2010; 28: 470–489.

67. Feng GC, Lin Z, Ou W, et al. A model-based meta-analysis of willingness to participate in cancer screening. *Int J Environ Res Public Health* 2021; 18: 2580.

68. Li L and Bautista JR. Elaboration, cancer worry, and risk perception mediate the association between news attention on the internet and intention to uptake HPV vaccination: extending the cognitive mediation model. *Int J Commun* 2021; 15: 22.

69. Curry SJ, Krist AH, Owens DK, et al. Screening for cervical cancer: US preventive services task force recommendation statement. *Jama* 2018; 320: 674–686.

70. Obstetricians ACO and Gynecologists. Annual mammograms now recommended for women beginning at age 40. Retrieved January 2011; 2013, vol. 4.

71. Nie Z, Gao S, Chen L, et al. Social media use and mental health among older adults with multimorbidity: the role of self-care efficacy. *J Am Med Inform Assoc* 2024; 31: 2210–2216.

72. Hayes A. *Introduction to mediation, moderation, & conditional process analysis (first)*. New York, NY, USA: The Guilford Press, 2013.

73. Cohen J, Cohen P, West SG, et al. *Applied multiple regression/correlation analysis for the behavioral sciences*. New York, NY, USA: Routledge, 2013.

74. Liu PL, Zhang L, Ma X, et al. Communication matters: the role of patient-centered communication in improving old adults' health competence and health outcomes. *Health Commun* 2024; 39: 363–375.

75. Zhang L, Ao SH, Ye JF, et al. How does health communication on social media influence e-cigarette perception and use? A trend analysis from 2017 to 2020. *Addict Behav* 2024; 149: 107875.

76. Stellefson M, Paige SR, Chaney BH, et al. Evolving role of social media in health promotion: updated responsibilities for health education specialists. *Int J Environ Res Public Health* 2020; 17: 1153.

77. Senjam SS, Manna S and Bascaran C. Smartphones-based assistive technology: accessibility features and apps for people with visual impairment, and its usage, challenges, and usability testing. *Clin Optometry* 2021; 13: 311–322.

78. Yang H, Yu J, Zo H, et al. User acceptance of wearable devices: an extended perspective of perceived value. *Telemat Inform* 2016; 33: 256–269.

79. Spanakis EG, Santana S, Tsiknakis M, et al. Technology-based innovations to foster personalized healthy lifestyles and well-being: a targeted review. *J Med Internet Res* 2016; 18: e128.

80. Kemp E, Trigg J, Beatty L, et al. Health literacy, digital health literacy and the implementation of digital health technologies in cancer care: the need for a strategic approach. *Health Promot J Austr* 2021; 32: 104–114.

81. Chien S-Y, Chuang M-C and Chen I-P. Why people do not attend health screenings: factors that influence willingness to participate in health screenings for chronic diseases. *Int J Environ Res Public Health* 2020; 17: 3495.

82. Halpern MT, Romaire MA, Haber SG, et al. Impact of state-specific Medicaid reimbursement and eligibility policies on receipt of cancer screening. *Cancer* 2014; 120: 3016–3024.

83. Agrawal P, Chen TA, McNeill LH, et al. Factors associated with breast cancer screening adherence among church-going African American women. *Int J Environ Res Public Health* 2021; 18: 8494.

84. Douthit N, Kiv S, Dwolatzky T, et al. Exposing some important barriers to health care access in the rural USA. *Public Health* 2015; 129: 611–620.

85. Miller MJ. Impact of COVID-19 on cervical cancer screening rates among women aged 21–65 years in a large integrated health care system—Southern California, January 1–September 30, 2019, and January 1–September 30, 2020. *MMWR Morbidity and Mortality Weekly Report* 2021; 70: 109–113.

86. Leach CR, Kirkland EG, Masters M, et al. Cancer survivor worries about treatment disruption and detrimental health outcomes due to the COVID-19 pandemic. *J Psychosoc Oncol* 2021; 39: 347–365.

87. DeGroff A, Miller J, Sharma K, et al. COVID-19 impact on screening test volume through the national breast and cervical cancer early detection program, January–June 2020, in the United States. *Prev Med* 2021; 151: 106559.

88. Zhou X, Krishnan A and Dincelli E. Examining user engagement and use of fitness tracking technology through the lens of technology affordances. *Behav Inf Technol* 2022; 41: 2018–2033.

89. HPV Information Center. United of States of America, human papillomavirus and related cancer, fact sheet 2021, https://hpvcentre.net/statistics/reports/USA_FS.pdf (2013, 2023).

90. Buskwofie A, David-West G and Clare CA. A review of cervical cancer: incidence and disparities. *J Natl Med Assoc* 2020; 112: 229–232.

91. Yoo W, Kim S, Huh WK, et al. Recent trends in racial and regional disparities in cervical cancer incidence and mortality in United States. *PloS one* 2017; 12: e0172548.

92. Lee BC, Xie J, Ajisafe T, et al. How are wearable activity trackers adopted in older adults? Comparison between subjective adoption attitudes and physical activity performance. *Int J Environ Res Public Health* 2020; 17: 3461.

93. Kalantari M. Consumers' adoption of wearable technologies: literature review, synthesis, and future research agenda. *Int J Technol Market* 2017; 12: 274–307.

94. Henriksen A, Woldaregay AZ, Muzny M, et al. Dataset of fitness trackers and smartwatches to measuring physical activity in research. *BMC Res Notes* 2022; 15: 258.

95. Rajaram S and Gupta B. Screening for cervical cancer: choices & dilemmas. *Indian J Med Res* 2021; 154: 210–220.

96. Hawkes D, Keung MH, Huang Y, et al. Self-collection for cervical screening programs: from research to reality. *Cancers (Basel)* 2020; 12: 1053.

97. Maver P and Poljak M. Primary HPV-based cervical cancer screening in Europe: implementation status, challenges, and future plans. *Clin Microbiol Infect* 2020; 26: 579–583.

98. Friedewald SM, Rafferty EA, Rose SL, et al. Breast cancer screening using tomosynthesis in combination with digital mammography. *Jama* 2014; 311: 2499–2507.

99. Qi J, Yang P, Min G, et al. Advanced internet of things for personalised healthcare systems: a survey. *Pervasive Mob Comput* 2017; 41: 132–149.

100. Chen M, Ma Y, Li Y, et al. Wearable 2.0: enabling human-cloud integration in next generation healthcare systems. *IEEE Commun Mag* 2017; 55: 54–61.

101. Lapointe L, Ramaprasad J and Vedel I. Creating health awareness: a social media enabled collaboration. *Health Technol (Berl)* 2014; 4: 43–57.

102. Lundgren RE and McMakin AH. *Risk communication: a handbook for communicating environmental, safety, and health risks*. Hoboken, NJ, USA: John Wiley & Sons, 2018.

103. Larsson M. A descriptive study of the use of the internet by women seeking pregnancy-related information. *Midwifery* 2009; 25: 14–20.

104. Zhou L, Zhang D, Yang CC, et al. Harnessing social media for health information management. *Electron Commer Res Appl* 2018; 27: 139–151.

105. Khaleel I, Wimmer BC, Peterson GM, et al. Health information overload among health consumers: a scoping review. *Patient Educ Couns* 2020; 103: 15–32.

106. Schmitt JB, Debbelt CA and Schneider FM. Too much information? Predictors of information overload in the context of online news exposure. *Inf Commun Soc* 2018; 21: 1151–1167.

107. Islam A, Whelan E and Brooks S. Social media overload and fatigue: the moderating role of multitasking computer self-efficacy. 2018.

108. Stevens HR, Oh YJ and Taylor LD. Desensitization to fear-inducing COVID-19 health news on twitter: observational study. *JMIR Infodemiol* 2021; 1: e26876.

109. Chae J. Who avoids cancer information? Examining a psychological process leading to cancer information avoidance. *J Health Commun* 2016; 21: 837–844.

110. Society AC. The missing member of the breast cancer team: breast-self examination. 1950, pp.30–31.

111. Society AC. Keeping up with cancer: digests from current literature of special importance in diagnosis and treatment. 1952, pp.38–45.

112. Lyttle NL and Stadelman K. Peer reviewed: assessing awareness and knowledge of breast and cervical cancer among Appalachian women. *Prev Chronic Dis* 2006; 3: 1–9.

113. Bennett IM, Chen J, Soroui JS, et al. The contribution of health literacy to disparities in self-rated health status and preventive health behaviors in older adults. *Ann Fam Med* 2009; 7: 204–211.

114. Hale TM. Is there such a thing as an online health lifestyle? Examining the relationship between social status, internet access, and health behaviors. *Inf Commun Soc* 2013; 16: 501–518.

115. You M-A, Baek EB and Kang N-G. The influences of mother's eHealth literacy, health information orientation, and social support on the use of internet on health promotion behaviors for their children. *J Health Inf Stat* 2021; 46: 221–229.

116. Manganello J, Gerstner G, Pergolino K, et al. The relationship of health literacy with use of digital technology for health information: implications for public health practice. *J Public Health Manag Pract* 2017; 23: 380–387.