What Functions of Smartphone Apps and Wearable Devices Promote Physical Activity? Six-Month Prospective Study on Japanese-Speaking Adults

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Submitted to: JMIR mHealth and uHealth
on: April 19, 2024

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Abstract

Background: Smartphone apps and wearable activity trackers are expected to play an important role in promoting physical activity (PA). Although studies suggest that use of commercial mobile health tools is associated with increased PA levels, most of the evidence is of a cross-sectional design, and thus longitudinal evidence is lacking.

Objective: Therefore, we aimed to reveal the app-use patterns that are prospectively associated with increases in and maintenance of PA. We were specifically interested in (a) whether continued app use is associated with adherence to the recommended levels of PA (i.e., 23 METs-h/w for adults or 10 METs-h/w for people aged>65 years) during a follow-up assessment and (b) whether any functions and features of PA apps predict the changes in PA level.

Methods: A two-wave longitudinal survey was conducted with the baseline and follow-up assessments separated by six months. A total of 20,573 Japanese-speaking online respondents participated in the baseline, among which 16,286 (8,289 women; mean age=54.7, standard deviation=16.8) completed the follow-up. On each assessment occasion, participants reported their current PA levels and whether they were using any PA apps and wearables. Each participant was then classified into following four categories: continued users (those who were using apps at both the baseline and follow-up; n=2,150, 13.2%), new users (those who started using apps before the follow-up; n=1,462, 9.0%), discontinued users (those who had been using apps at the baseline but not anymore at the follow-up; n=1,899, 11.7%), and continued nonusers (those who had never used apps; n=10,775, 66.2%).

Results: Most continued users (n=1,538, 71.5%) improved or maintained their PA to the recommended levels over six months; however, discontinued users showed the largest reduction in PA (-7.95 METs-h/w on average), and most failed to meet the recommended levels at the follow-up. Analyses of individual app functions showed that energy analysis (e.g., app calculation of daily energy expenditure) and journaling (e.g., users manually entering notes and maintaining an exercise diary) were significantly associated with increases in PA (odds ratio [OR]=1.67, 95% confidence interval [CI] [1.05, 2.64] and OR=1.76, 95%CI [1.12, 2.76], respectively). On the other hand, those who maintained the recommended PA levels at the follow-up typically used the goal setting (OR=1.73, 95%CI [1.21, 2.48]), sleep information (OR=1.66, 95%CI [1.03, 2.68]), and blood-pressure recording (OR=2.05, 95%CI [1.10, 3.83]) functions.

Conclusions: The results support the importance of continued app use in increasing and maintaining PA levels. Different app functions may be suited to increasing PA (e.g., goal setting and journaling) vs. maintaining high levels of PA (their health in general, covering sleep and blood pressure, not limited to PA).

(JMIR Preprints 19/04/2024:59708)
DOI: https://doi.org/10.2196/preprints.59708

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Paper type: Original paper
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Background: Smartphone apps and wearable activity trackers are expected to play an important role in promoting physical activity (PA). Although studies suggest that use of commercial mobile health tools is associated with increased PA levels, most of the evidence is of a cross-sectional design, and thus longitudinal evidence is lacking.
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Conclusions: The results support the importance of continued app use in increasing and maintaining PA levels. Different app functions may be suited to increasing PA (e.g., goal setting and journaling) vs. maintaining high levels of PA (their health in general, covering sleep and blood pressure, not limited to PA).

Keywords: mobile health; smartphone app; physical activity; wearable activity tracker; longitudinal design

Introduction

Background

Physical inactivity is highly prevalent in modern society, and its average proportion is 31% worldwide [1]. Physical inactivity is known to be associated with noncommunicable diseases such as stroke, hypertension, and diabetes [2] and is now the fourth leading risk of mortality [3]. To improve physical activity (PA), several behavior change techniques (BCTs) have been developed [4], which are provided by healthcare professionals and are distributed via digital tools including smartphones and wearable activity trackers. These digital, mobile-health (mHealth) interventions are expected to play a pivotal role in PA promotion, particularly during and after the COVID-19 pandemic when in-person contact is highly restricted. These digital PA tools typically offer measuring and monitoring (e.g., activity log), information and analysis (e.g., progress and individual exercise data), and support and feedback (e.g., advice on PA and goal setting) [5]. The most frequently implemented BCTs are self-monitoring, providing feedback on performance, and goal-setting [6]. Observational studies have found that fitness app users are more physically active than nonusers [7], and app users have approximately twice the odds of meeting aerobic PA guidelines compared to nonusers even during the COVID-19 pandemic [8]. One important limitation of the literature is that most studies on PA apps (and healthcare apps in general) used a cross-sectional design; thus, longitudinal evidence is still lacking. We aimed to fill this gap and reveal whether and how daily use of PA apps and wearables (not necessarily as part of a clinical intervention or treatment) is prospectively associated with increased levels of PA.

How Effective is an mHealth Intervention? Evidence from Clinical Trials

A large number of randomized or nonrandomized trials have been published on this topic, which are not limited to daily uses of commercial PA apps and wearables. As far as we know, three umbrella reviews have been conducted, targeting digital interventions for improving PA. An early umbrella review [9] synthesized 11 systematic reviews and meta-analyses on eHealth or mHealth interventions targeting PA, sedentary behavior, and healthy eating for healthy individuals. The authors concluded that a majority of e/mHealth interventions were reported to be effective, but high heterogeneity was found across multiple studies. Another umbrella review [10] focused on interventions using wearable activity trackers to improve PA, and a synthesis of 39 systematic reviews and meta-analyses indicated a moderate effect size (standardized mean difference=0.3-0.6). A more recent umbrella review [11] identified 17 systematic reviews and meta-analyses on digital interventions specifically targeting PA and sedentary behavior to prevent or manage noncommunicable diseases. The results suggest that digital interventions have a small to moderate effect on increasing PA, although heterogeneity is documented across multiple reviews. For example, three systematic reviews concluded that mHealth interventions are effective (involving gamification [12] or personalization [13] and delivered in workplace settings [14]) whereas a meta-analysis [15] found no significant effects of mobile interventions on total PA, moderate to vigorous PA, and walking. Similarly, a review on mHealth interventions equipped with social features found a non-significant effect on PA outcomes [16].

Researchers have also explored specific components or features of apps and wearables that are the key to improving PA. Apps and digital interventions offering richer content and a larger number of BCTs are found to be more favored by users [17] and are associated with better health outcomes [18,19], although users also appreciate simplicity (e.g., being intuitive to use) [20]. Researchers also found that specific app features and characteristics are more favored than are others, such as export of data, usability, and cost [20]; tracking (e.g., steps, heart rate, and ovulation) [21,22]; and health information and medical reminders [23]. However, the umbrella reviews [9,11] concluded that evidence for the effectiveness of specific BCTs or combinations of BCTs in digital PA interventions is largely mixed. In search of successful digital implementations of BCTs, meta-regressions and systematic reviews highlighted the importance of behavioral goals and self-monitoring [24]; text-messaging, personalization, goals and planning, and graded tasks [25]; goal setting, prompts/cues, feedback on behavior, and action planning [26]; and personalized goal setting and motivational feedback [27]. In contrast, several meta-analyses reported no significant associations between intervention efficacy and the number or types of implemented BCTs [28,29].

Note that these analyses typically targeted clinical trials on a specific population, such as patients, older adults, and individuals with low socioeconomic status. Few studies investigated how spontaneous uses of commercial apps and wearables can help improve PA in a community sample. Investigating app uses in uncontrolled settings is of particular importance to gauge the potential efficacy of PA apps and wearables on the market, as studies highlighted substantial differences in users' behavior in more controlled, clinical contexts; for example, the average retention rate of mHealth interventions is about 91% in published randomized controlled trials [25], which is surprisingly high compared with the user engagement observed for commercial healthcare apps (e.g., 4%, the median percentage of daily active users of mental health apps [30]). An exceptional longitudinal study [31] investigated user engagement in a commercial app rewarding users with digital incentives for walking, and the results showed that 60% of the participants engaged with the app for at least six months. Interestingly, users who actively engaged with the app showed larger increases in daily step count than less frequent users did. These findings highlight the importance of continuous, long-term use of PA apps or wearables for users to benefit from these digital tools.

Objectives

This study aimed to reveal the app-use patterns prospectively associated with increased levels of PA. To achieve this aim, we conducted a two-wave longitudinal survey with a six-month interval. At each survey occasion, participants reported their current levels of PA as well as whether they were using any PA apps and wearables. Each participant was then classified into the following four categories: continued users (those who were using apps or wearables at both the baseline and follow-up), new users (those who started using apps before the follow-up), discontinued users (those who had used apps at the baseline but not anymore at the follow-up), and continued nonusers (those who had never used apps). We were specifically interested in (a) whether the continued and new users would increase their PA level or maintain high-level PA up to the six-month follow-up and (b) whether any functions and features of the PA apps would predict the increases in PA. Our recent cross-sectional study found that people typically used a limited number of functions (median: two functions, interquartile range [1,4]) within an app, and physically active users tended to use functions such as sensor information (e.g., step count and heart rate), goal setting (e.g., to set one's daily step goal), energy analysis (e.g., estimation of the calories consumed), journaling (e.g., manual recording of daily exercise), and global positioning system (GPS)/maps. We did not have a specific hypothesis concerning the prospective effects of individual app functions, and thus the overall analyses were conducted in an exploratory manner. Yet, we expected that sensor information (closely related to self-monitoring/tracking in the BCT taxonomy) and some other functions implementing regulatory techniques [32] would be associated with increases in PA. Moreover, we expected that the number of functions might be associated with PA increases, as some (but not all) studies suggested that the amount of app content or number of implemented BCTs is associated with the efficacy of mobile interventions [18,19].

Method

Participants and Procedure

Participants were recruited from the sample of respondents who completed the first (hereafter, baseline) survey, the results of which have been published elsewhere [33,34]. The baseline survey was conducted in 2023, where N=20,573 online respondents (residents in Japan who had been registered in a database of potential participants for online surveys) completed the questionnaires concerning general health and health-related behaviors, including PA levels and use of mHealth apps. Age (>18 years) was the eligibility criterion, and good knowledge of the Japanese language was assumed as the survey was written in Japanese. All these participants were invited to the second (hereafter, follow-up) survey, which took place approximately six months after the baseline survey. The follow-up survey was completed by n=16,286 participants, who received a small compensation for each survey (online shopping voucher; value: approximately 0.31 USD). The study protocol was approved by the Ethics Committee of the National Institute of Advanced Industrial Science and Technology (approval ID: 2022-1279).

Measures

International Physical Activity Questionnaire-Short Form

Participants indicated how many days and minutes (per day) they engaged in (a) walking, (b) moderate-intensity activity, and (c) vigorous-intensity activity over an average week [35,36]. The reported duration and frequency of each activity were multiplied and converted into metabolic equivalents (METs-hour per week). The MET score was then dichotomized to represent adherence to the national PA recommendations: 23 METs-h/w for adults aged <65 and 10 METs-h/w for older adults [37].

Stages of Change Questionnaire

Participants completed the Japanese version [38] of the Stages of Change questionnaire for PA [39,40]. The questionnaire asks participants to indicate the most applicable among the following five statements: *I currently do not exercise and do not intend to start exercising in the future* (Precontemplation); *I currently do not exercise but I am thinking about starting to exercise in the next six months* (Contemplation); *I currently exercise some, but not regularly* (Preparation); *I currently exercise regularly, but have only begun doing so within the last six months* (Action); and *I currently exercise regularly and have done so for longer than six months* (Maintenance). Regular exercise was explicitly defined in the questionnaire instruction as performing PA for a set of 20 min or longer twice or more per week.

Use of Apps and Wearables

At the baseline, participants provided a binary response indicating whether they used any apps or wearables to support their PA and exercise. Upon receiving an affirmative response, participants were further asked to provide details about how they used the apps and wearables. The questions covered the duration and frequency of app use (how long and frequently they had used/were using the apps) as well as the functions and features of the apps in use. Participants were presented with a list of 41 app functions (e.g., sensor information, goal setting, and energy analysis) [33], and they indicated any applicable functions they were using [20,29]. However, as most of the listed functions were rarely used [33], we exclusively focused on the most frequently used functions for the current analyses: sensor information (e.g., step count and heart rate), goal setting and goal progress (e.g., steps achieved), energy analysis (e.g., estimated daily energy expenditure), weight recording, journaling (e.g., diary or notes that are manually entered), GPS/map, sleep information, reward points, and blood-pressure recording.

At the six-month follow-up, participants completed a similar questionnaire asking whether they were using apps and wearables. Unlike the baseline, participants were presented with the following three response options: (a) have been using apps and wearables for the past six months; (b) used them previously but not anymore; and (c) have not used any app or wearable. Further questions concerning individual app functions and features were omitted due to limited space in the follow-up survey.

Responses made at the baseline and follow-up were interpreted as a 2×2 factorial matrix (user vs. nonuser; baseline vs. follow-up), according to which each participant was classified into four categories: new users, continued users, discontinued users, and continued nonusers. Those who indicated that they had used but were not using apps or wearables anymore at the follow-up, that is, who selected option (b), were counted in discontinued users (n=1,396, 8.14%). Some of these participants were nonusers at the baseline and used apps or wearables only temporally between the baseline and follow-up (n=851, 4.97%); their data were excluded from the analyses for ease of interpretation.

Statistical Analyses

We first explored demographic and descriptive differences between the four types of (non)users based on gender, age, education level, household income, and PA level and readiness. Second, to examine how (dis)continued app use is associated with changes in PA level, logistic regression analyses were conducted. Two binary dependent variables were used, representing the contrasts (a) between individuals who maintained under-recommended levels of PA (<23 or 10 METs) at the six-month follow-up vs. those who showed increases in PA to the recommended or higher levels over time and (b) between individuals who maintained the recommended PA levels vs. those who showed decreases and did not meet the recommended levels anymore at the follow-up. We also calculated simple change scores for PA (follow-up minus baseline) to clarify the magnitude of change each type of (non)user experienced over time. Finally, two independent logistic regression analyses were conducted, predicting the two binary dependent variables, namely changes in (and maintenance of) adherence to the recommended PA levels, according to individual app features and functions in use at the baseline. All analyses were conducted using R (version 4.2.2) with the following specific packages: chisq.posthoc.test [41], finalfit [42], ggpubr [43], and tidyverse [44].

Results

Demographics

Table 1 shows the demographic characteristics for each type of app (non)user. We identified 1,462 (9.0%) new users, 2,150 (13.2%) continued users, 1,899 (11.7%) discontinued users, and 10,775 (66.2%) continued nonusers in the dataset. Among those who had been using apps or wearables at the baseline (n=3,612), 59.5% (n=2,150) reported that they continued their usage at the follow-up. A one-way analysis of variance indicated significant age differences between the user types (partial η^2=.009, P<.001), implying that new users were older than continued users and continued nonusers, and discontinued users were the youngest among the four types of users (P<0.001; adjusted by Tukey's method). Chi-square tests and residual analyses revealed significant gender differences: Continued users were more likely to be men (60.2%) than women (39.8%; P<.001), whereas continued nonusers were more likely to be women (53.5%) than men (46.5%; P<.001). Moreover, continued users were the most prevalent among individuals with the highest household income (≥10 million JPY) and education level (university or above). At the baseline, most continued users (77.9%; n=1,609 of 2,150) reported that they had been using an app for longer than six months (about 64.0% for discontinued users; n=1,128 of 1,899). Similarly, most continued users (80.1%; n=1,654 of 2,150) reported using a PA app once or more each day (about 65.5% for discontinued users; n=1,153 of 1,899).

Table 1. Demographic statistics of users and nonusers

Variable	Current app user		Current nonuser		Total N=6,286	Statistics and *P*-value
	Continued user (user at baseline) N=2,150	New user (nonuser at baseline) N=1,462	Discontinued user (user at baseline) N=1,899	Continued nonuser (nonuser at baseline) N=10,775		
Age (years), mean (SD[a])	53.8 (16.3)	57.3 (16.8)	50.9 (17.3)	55.2 (16.7)	54.7 (16.8)	F(3, 16,282)=50.16, P<.001
Age (categorical), n (%)						χ2(9)=161.86, P<.001
<30	203 (9.4)	126 (8.6)	250 (13.2)	965 (9.0)	1,544 (9.5)	
30-44	452 (21.0)	226 (15.5)	502 (26.4)	2,093 (19.4)	3,273 (20.1)	
45-59	596 (27.7)	333 (22.8)	472 (24.9)	2,859 (26.5)	4,260 (26.2)	
≥60	899 (41.8)	777 (53.1)	675 (35.5)	4,858 (45.1)	7,209 (44.3)	
Women, n (%)	855 (39.8)	749 (51.2)	915 (48.2)	5,770 (53.5)	8,289 (50.9)	χ2(3) =142.56, P<.001
BMI[a], mean (SD)	22.4 (3.5)	22.3 (3.9)	22.3 (3.8)	22.0 (3.7)	22.1 (3.7)	F(3, 16,282)=7.27, P<.001
Married, n (%)	1,497 (69.6)	964 (65.9)	1,213 (63.9)	6,846 (63.5)	10,520 (64.6)	χ2(3) =30.68, P<.001
Child/children[b], n (%)	1,412 (65.7)	984 (67.3)	1,211 (63.8)	6,782 (62.9)	10,389 (63.8)	χ2(3) =14.48, P =.002
Education level, n (%)						χ2(12)=231.79, P<.001
Middle school	27 (1.3)	36 (2.5)	38 (2.0)	290 (2.7)	391 (2.4)	
High school	517 (24.0)	453 (31.0)	531 (28.0)	3,546 (32.9)	5,047 (31.0)	
College or vocational school	382 (17.8)	287 (19.6)	441 (23.2)	2,572 (23.9)	3,682 (22.6)	
University or above	1,210 (56.3)	673 (46.0)	864 (45.5)	4,293 (39.8)	7,040 (43.2)	
Other	14 (0.7)	13 (0.9)	25 (1.3)	74 (0.7)	126 (0.8)	
Job[a], n (%)	27 (1.3)	36 (2.5)	38 (2.0)	290 (2.7)	391 (2.4)	χ2(3)=146.85, P<.001
Household income, n (%)						
<3 million JPY[c]	322 (15.0)	320 (21.9)	416 (21.9)	2,487 (23.1)	3,545 (21.8)	χ2(15)=335.43, P<.001
3-5 million JPY	496 (23.1)	350 (23.9)	455 (24.0)	2,656 (24.6)	3,957 (24.3)	
5-7 million JPY	365 (17.0)	228 (15.6)	295 (15.5)	1,550 (14.4)	2,438 (15.0)	

7-10 million JPY	360 (16.7)	179 (12.2)	236 (12.4)	1,135 (10.5)	1,910 (11.7)	
≥10 million JPY	314 (14.6)	115 (7.9)	183 (9.6)	701 (6.5)	1,313 (8.1)	
No response	293 (13.6)	270 (18.5)	314 (16.5)	2,246 (20.8)	3,123 (19.2)	
Physical activity (baseline, METs-h/w[d]), median (IQR[e])	34.6 (16.5 to 67.1)	23.3 (9.9 to 49.6)	23.3 (7.7 to 53.5)	11.6 (0.6 to 33.0)	16.5 (3.3 to 41.7)	$\chi2(3)=1,239$, $P<.001$
Physical activity (follow-up, METs-h/w[f]), median (IQR)	34.0 (16.2 to 65.2)	24.2 (11.6 to 51.7)	16.5 (2.5 to 43.1)	9.9 (0.0 to 29.7)	14.8 (1.1 to 38.1)	$\chi2(3)=1,419.6$, $P<.001$

[a] Standard deviation
[b] Data are from a follow-up survey.
[c] 1 USD=140 JPY
[d] Metabolic equivalent of tasks, hours per week.
[e] Interquartile range
[f] Health enhancing physical activity

Relationship between App Use and Adherence to the Recommended PA Level

Table 2 illustrates changes in PA level for each user type over six months. Continued nonusers typically maintained under-recommended levels of PA over time (n=5,259, 48.8%), whereas new users were most likely to increase PA to the recommended level (n=178, 12.2%). Continued users typically maintained the recommended PA levels over time (n=1,327, 61.7%), whereas discontinued users most likely failed to adhere to the recommended level at the follow-up (n=330, 17.4%) among the four user types.

Table 2. Frequency of (non)users who maintained or did not maintain the recommended physical-activity (PA) level

PA change category (Baseline → Follow-up)	Current user		Current nonuser	
	Continued user (%)	New user (%)	Discontinued user (%)	Continued nonuser (%)
Maintained under-recommended level (not adhered → not adhered)	390 (18.1)	370 (25.3)	638 (33.6)	5,259 (48.8)
Increased (not adhered → adhered)	211 (9.8)	178 (12.2)	159 (8.4)	931 (8.6)
Decreased (adhered → not adhered)	222 (10.3)	144 (9.8)	330 (17.4)	1,269 (11.8)
Maintained recommended level (adhered → adhered)	1,327 (61.7)	770 (52.7)	772 (40.7)	3,316 (30.8)

Note. Adherence to the recommended PA level: equal to or larger than 23 METs-h/w for adults or 10 METs-h/w for older adults aged ≥ 65 years. MET=metabolic equivalent of tasks, hours per week.

Logistic regression analyses were performed to examine how (dis)continued app use is associated with adherence to the recommended PA level (23 or 10 METs-h/w) over six months. Results (Table 3) showed that compared to discontinued users, continued users (odds ratio [OR]=2.171, 95% confidence interval [CI] [1.71, 2.76], P<.001) and new users (OR=1.93, 95% CI[1.50, 2.48], P<.001) were more likely to increase PA to the recommended levels at the follow-up. Continued nonusers, compared to discontinued users, were more likely to maintain under-recommended PA levels at the follow-up (OR=0.71, 95%CI [0.59, 0.86], P<.001). Another logistic regression analysis (distinguishing between people who maintained the recommended levels vs. decreased PA to the under-recommended levels) showed that continued users (OR=2.56, 95% CI [2.11, 3.10], P<.001) and new users (OR=2.29, 95% CI [1.84, 2.85], P<.001) were more likely to maintain the recommended PA levels compared to discontinued users. Continued nonusers did not significantly differ from discontinued users (OR=1.12, 95% CI [0.97, 1.29], P=.113).

Table 3. Logistic regressions predicting physical activity changes based on 23 (or 10) METs-h/w[a]

IV[b] (app function)	Estimate	*SE*[c]	z	*P*	OR[d]	95%CI[e]
DV[f] contrast: Increased to vs. maintained at below the recommended level (n=8,136)						
Intercept (reference: discontinued	-1.389	0.089	-15.675	<.001	0.249	[0.209, 0.297]

user)						
Continued user	0.775	0.123	6.296	<.001	2.171	[1.705, 2.763]
New user	0.658	0.127	5.171	<.001	1.930	[1.504, 2.477]
Continued nonuser	-0.342	0.096	-3.581	<.001	0.710	[0.589, 0.857]
DV contrast: Maintained the recommended level vs. decreased (n=8,150)						
Intercept (reference: discontinued user)	0.850	0.066	12.922	<.001	2.339	[2.056, 2.661]
Continued user	0.938	0.098	9.583	<.001	2.555	[2.109, 3.096]
New user	0.827	0.112	7.374	<.001	2.286	[1.835, 2.847]
Continued nonuser	0.111	0.074	1.503	.133	1.117	[0.967, 1.290]

[a] Metabolic equivalent of tasks, hours per week
[b] Independent variable
[c] Standard error
[d] Odds ratio
[e] Confidence interval
[f] Dependent variable

Changes in PA Level at the Six-month Follow-Up

We then calculated the simple change scores of PA levels (i.e., follow-up minus baseline in METs-h/w) to estimate the large changes each type of users experienced over six months (Figure 1). New users were the only group that showed increases in PA level (M=1.71, SD= 57.76), which was significantly larger than the changes (decreases) that continued nonusers experienced [M=-2.95, SD= 50.76; t(1,780.5)=2.94, P=.003]. Continued users showed decreases in PA on average (M=-3.85, SD= 58.53), but discontinued users exhibited even larger decreases [M=-7.95, SD= 60.52; t(3949.1)=2.19, P=.029]. These results suggest that those who recently started to use apps and wearables improved their PA level the most. On the other hand, continued app use helped maintain their PA levels (although slight decreases were observed), as discontinuation leads to a substantial reduction in PA level (equivalent to reduction by >1 h of vigorous PA per week [45]).

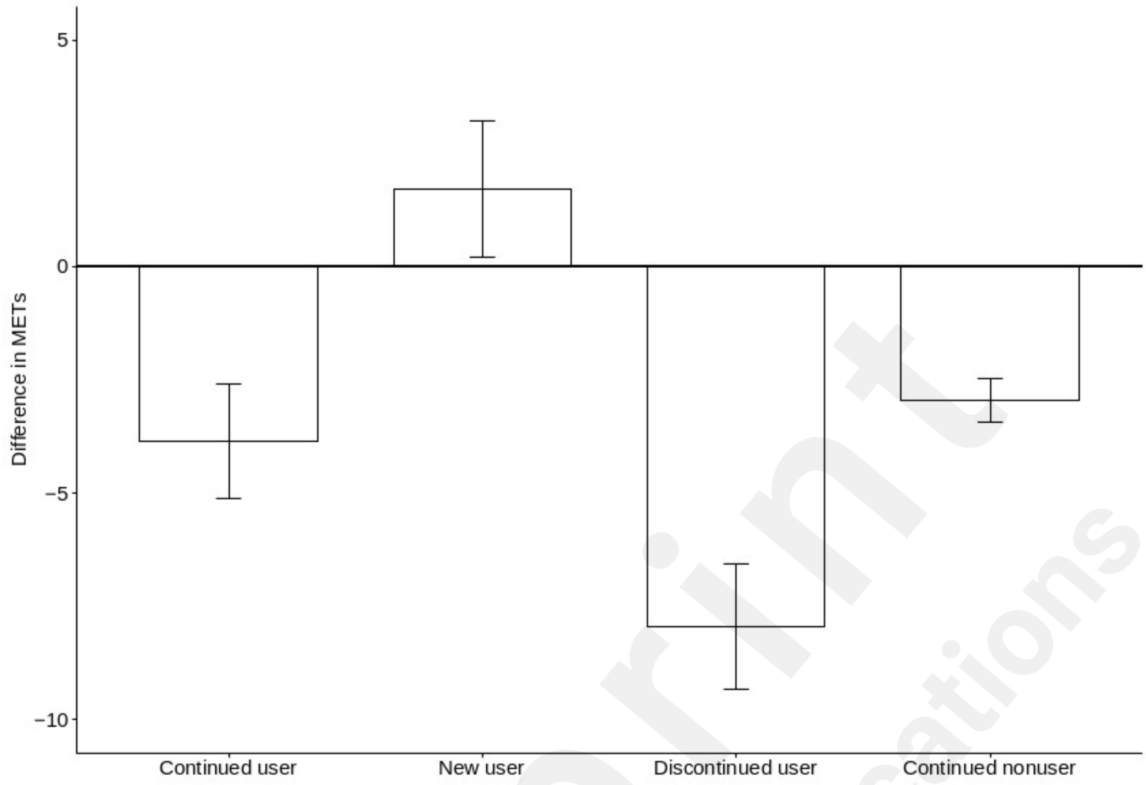

Figure 1. Change in physical activity level (in METs-h/w) at the six-month follow-up among the four types of (non)users. Error bar indicates the standard error. METs-h/w=metabolic equivalent of tasks, hours per week.

Function-Wise Analyses Predicting Changes in PA

App users (1,342 continued users, 65.0%; 870 discontinued users, 49.4%) reported using sensor information most frequently, which was followed by goal setting, goal progress, energy analysis, and weight recording (see Tabel S1 for details). To explore which app functions are associated with an increase in or maintenance of PA levels, we estimated two logistic regression models, where changes in PA level (increase to vs. maintenance below the recommended level; maintenance above the recommended level vs. decrease to the under-recommended level) were predicted by individual app functions used at the baseline. These analyses targeted continued users exclusively (i.e., individuals who reported using apps at both the baseline and follow-up), and nonusers were excluded. Results (Table 4) showed that energy analysis and journaling were significantly associated with increases in PA to the recommended levels (OR=1.67, 95%CI [1.05, 2.64] and OR=1.76, 95%CI [1.12, 2.76], respectively). On the other hand, maintenance of the recommended levels (vs. decrease to the under-recommended levels) was predicted by goal setting (OR=1.73, 95%CI [1.21, 2.48]), sleep information (OR=1.66, 95%CI [1.03, 2.68]), and blood-pressure recording (OR=2.05, 95%CI [1.10, 3.83]). We also tested the association between the number of app functions in use (at baseline) and changes in PA level (simple change score, i.e., follow-up minus baseline) among continued users, which did not reach statistical significance (r=-0.02, P=.481).

Table 4. Logistic regression predicting physical activity change based on 23 METs-h/w[a]

IV[b] (app function)	Estimate	*SE*[c]	z	*P*	OR[d]	95%CI[e]
DV[f] contrast: Increased to vs. maintained at below the recommended level; n=601						
Show sensor info	0.008	0.191	0.040	0.968	1.008	[0.694, 1.464]
Goal setting	0.005	0.223	0.023	0.982	1.005	[0.649, 1.557]
Show goal progress	0.217	0.232	0.937	0.349	1.243	[0.789, 1.957]
Energy analysis	0.510	0.235	2.172	0.030	1.665	[1.051, 2.637]
Weight recording	-0.243	0.257	-0.944	0.345	0.785	[0.474, 1.299]
Journaling	0.562	0.231	2.434	0.015	1.755	[1.116, 2.760]
GPS[g]/map	-0.081	0.248	-0.326	0.745	0.922	[0.567, 1.500]
Show sleep info	-0.009	0.236	-0.039	0.969	0.991	[0.624, 1.573]
Reward points	0.300	0.273	1.098	0.272	1.350	[0.790, 2.308]
Blood-pressure recording	0.454	0.348	1.303	0.193	1.574	[0.795, 3.117]
DV contrast: Maintained the recommended level vs. decreased; n=1549						
Show sensor info	0.182	0.159	1.142	0.253	1.200	[0.878, 1.640]
Goal setting	0.548	0.184	2.979	0.003	1.729	[1.206, 2.480]
Show goal progress	0.267	0.190	1.406	0.160	1.307	[0.900, 1.897]
Energy analysis	-0.025	0.190	-0.131	0.896	0.975	[0.672, 1.416]
Weight recording	0.152	0.214	0.711	0.477	1.164	[0.766, 1.770]
Journaling	0.082	0.190	0.433	0.665	1.086	[0.748, 1.575]
GPS/map	0.395	0.221	1.790	0.073	1.484	[0.963, 2.287]
Show sleep info	0.506	0.246	2.060	0.039	1.658	[1.025, 2.684]
Reward points	0.120	0.242	0.495	0.621	1.127	[0.701, 1.812]
Blood-pressure recording	0.716	0.319	2.244	0.025	2.046	[1.095, 3.825]

[a] Metabolic equivalent of tasks, hours per week
[b] Independent variable
[c] Standard error
[d] Odds ratio
[e] Confidence interval
[f] Dependent variable
[g] Global positioning system

Discussion

Principal findings

This study investigated how likely users of commercial PA apps and wearables are to continue their usage up to a six-month follow-up, and how helpful continued app use is in increasing or maintaining PA levels. More than half (59.5%) of the app users identified at the baseline reported continuing the usage to the six-month follow-up. This retention rate may feel too high given the reported daily user engagements for healthcare apps [30], but it is comparable to the rate found in a longitudinal study on a commercial PA app, documenting a 60% active user engagement for six months [31]. Overall, the results support the importance of continued app use in maintaining PA levels: Most continued users (71.5%) maintained or improved their PA to the recommended levels over six months, whereas 51% of discontinued users failed to meet the recommended levels at the follow-up (either decreased or maintained low levels over time). Indeed, discontinued users showed the largest reduction in PA level among the four types of users, with the mean reduction of -7.95 METs-h/w.

Demographic Characteristics of Continued vs. Discontinued Users

Our analyses of the demographic characteristics of continued (vs. discontinued) users suggested that continued users were older and more likely to be men and had higher education levels and income. Former (cross-sectional) studies consistently found that m/eHealth users are younger, more educated, and have higher (digital) health literacy than nonusers do [46–48]. Educational attainment is thought to reflect literacy and skills (including confidence with the use of digital and smart devices) as well as social norms related to the perceived values of health [47]. In general, women are dominant users of healthcare apps (for diet, nutrition, and self-care), but fitness apps are an exception as they are more preferred by men [46]. Older people typically avoid new technology and mHealth services [49]. In contrast, our results indicated that older users were more likely to continue using apps. We do not have data that readily explain this unexpected effect. However, given that most of the continued users in our data had been using PA apps for long time (>6 months) already at the baseline, even older users may have had high self-efficacy and perceived ease of use, leading to less technology anxiety. Studies have pointed to various facilitators and barriers of technology adaptation for older people (e.g., personal experiences and subjective norms) [50], which may be a basis for future research to disentangle how older users successfully adapt and implement mHealth tools in their daily routine.

App Functions Predictive of an Increase in PA

We found that *energy analysis* and *journaling* were predictive of increases in PA to the recommended levels over six months; on the other hand, *goal setting*, *sleep information*, and *blood-pressure recording* were often used by people who maintained the recommended levels to the follow-up. We previously reported cross-sectional analyses on the associations between PA levels and individual app functions [51], which indicated that individuals with health enhancing PA typically reported using sensor information (e.g., step count and heart rate), goal setting, goal progress, energy analysis, journaling, and GPS/map. The current prospective analyses highlight the particular importance of energy analysis and journaling in improving PA over time. Note that sensor information was very common among PA-app users (Table S1); therefore, besides the automatically recorded PA data such as step count, users may benefit from additional analyses on physiological data (i.e., calculations on energy expenditure) and conscious or explicit engagements with the app (i.e., journaling, manually entering a log of daily exercise, and PA).

Interestingly, maintenance of the recommended PA level was associated with use of sleep information and blood-pressure recoding (as well as goal setting), which may suggest that users who are already sufficiently active appreciate functions that support healthcare in general, not necessarily targeting fitness and exercise. Published (meta-analytic) studies listed the key app components in enhancing PA, such as self-monitoring, goals and planning, prompts/cues, feedback on behavior, and action planning [24–27], most of which are designed and implemented to support PA. It might be important for future research to broadly explore app functions and aspects (not limited to PA-relevant functions), which may help identify more efficacious sets or packages of functions, particularly when the focus is on maintaining rather than increasing the PA level. This may echo the usefulness of the stages of changes [39,52] (e.g., to guide the best prescription for those identified at the action or maintenance stages) and the importance of tailoring (digital) behavior interventions.

Another interesting finding from the current analyses is that the reported number of app functions in use was not significantly associated with increases in PA over six months. Several studies have suggested that the amount of app content or the number of implemented BCTs is associated with efficacy of mHealth interventions [18,19], but this association has not necessarily been replicated [29]. Note that our analyses utilized self-report data and not on the actual log of user behavior; therefore, we cannot exclude the possibility that participants did not correctly and exhaustively report all the functions in use. However, our findings imply that (a) users may not be aware of every function implemented in an app (or at least, they do not use them all consciously), and (b) they do not necessarily benefit from multifunctionality and rather a limited number of functions (e.g., goal setting and journaling) may help improve PA efficiently. Indeed, it is known that users appreciate the simplicity of an app [20], and as Michie et al. [32] found, interventions that combine self-monitoring with at least one regulatory technique (e.g., goal setting) can be the most cost-effective (minimal) set of interventions.

Limitations

The results reported here should be interpreted carefully as they have several important limitations. First, we targeted Japanese-speaking adults exclusively, which may limit the generalizability of the findings. The apps and products on the Japanese e/mHealth market may differ from those in other regions and countries. Although we see similarities in the behavior of users from Japan and Western countries, it would be an interesting direction to explore country- or culture-specific aspects for future research. Second, we cannot exclude the possibility of sampling bias. We reported elsewhere [51] that the current sample showed higher PA levels than the general population in Japan, likely because the study was advertised as a survey on PA and health. Related to this point, attrition might be a source of bias, as approximately 20% of the participants dropped out to the follow-up. Third, we exclusively relied on the self-report of PA, which is not always consistent with objective measures, such as accelerometers. Similarly, user behavior and individual app-function uses can be monitored automatically or be made publicly available (e.g., [53]), although a downside of such an approach is that the analyses must be limited to a particular app or platform, with the generalizability of the results being sacrificed.

Conclusion

Notwithstanding these limitations, we believe that our findings are meaningful additions to the literature, highlighting the continued use of apps and wearables as the key to enhancing and maintaining high levels of PA. On the other hand, we found that around half of the users discontinued using apps/wearables in six months. We did not assess barriers preventing users from continuous engagements (e.g., [54,55]), which should be explored in future research to establish effective measures to maintain active user engagements.

Acknowledgements

This study was supported by JSPS KAKENHI (23H01051).

Conflicts of Interest

The authors declare no conflict of interest concerning the study reported in this article.

Abbreviations

BCT: behavior change technique
CI: confidence interval
DV: dependent variable

GPS: global positioning system
IQR: interquartile range
IV: independent variable
METs-h/w: metabolic equivalent of tasks, hours per week
mHealth: mobile health
OR: odds ratio
PA: physical activity
SD: standard deviation
SE: standard error

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Supplementary Files

Multimedia Appendixes

Number of users for each app function among continued and discontinued users.
URL: http://asset.jmir.pub/assets/2cce1cc40ae5e765926cf180d13adfcc.docx