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BRIEF REPORT

Factors associated with long-term wearable physical activity monitor user engagement

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Abstract

Wearable physical activity monitors (PAMs) have potential to positively influence physical activity. However, high rates of disengagement have been reported, which dampens enthusiasm, as these devices are unlikely to impact habitual physical activity if they are not worn for a sustained period of time. The purpose of this study was to identify demographic and device-use characteristics (e.g., data sharing) associated with sustained device engagement. Current PAM users (n = 418; mean age: 35.0 ± 12.5; 78% female) from across the USA were recruited online and completed a baseline web-based survey in 2015–2016 comprising questions about demographics and device use. Participants were followed-up again in 2017, at which time they reported whether or not they still used a PAM. Sustained PAM engagement was defined as those who continued use at follow-up. The median follow-up time was 15.5 (±3.7) months. In fully adjusted models, the following were significantly associated with long-term engagement: age (odds ratio [OR]: 1.03; 95% confidence interval [CI]: 1.01–1.05, p = .014), Hispanic ethnicity (OR: 3.67; 95% CI: 1.20–11.26, p = .023), running as a preferred exercise (OR: 1.82; 95% CI: 1.02–3.24, p = .043), wanting to monitor health variables as a reason for choosing to use a PAM (OR: 1.73; 95% CI: 1.02–2.92, p = .042), and sharing data from the PAM publicly on social media (e.g., Facebook and Twitter; OR: 5.11; 95% CI: 1.64–15.93, p = .005). A number of sociodemographic and use characteristics were associated with sustained device use over a median follow-up of 1.3 years. One modifiable factor that may lead to longer device engagement is encouraging users to share data publicly.

Keywords

Physical activity, Activity monitors, Social media, Social networks, Wearables

Implications

Practice: Users may engage with commercial wearable activity monitors for longer, thus offering a greater opportunity to impact their physical activity behaviors, if they are encouraged to share their data publicly.

Policy: Programs that consider physical activity monitors a potential means of changing health behaviors should explore ways in which users can connect with others so as to prolong device engagement.

Research: Additional research is needed to identify whether long-term use of physical activity monitors can result in improved health outcomes.

INTRODUCTION

Approximately 45% of U.S. adults report owning a wearable physical activity monitor (PAM), such as those made by Fitbit. The consumer PAM market continues to grow exponentially, with yearly global sales of over 200 million devices projected by 2021 [1,2]. As such, PAMs hold promise as a possible tool for low-cost, scalable intervention to tackle high rates of physical inactivity [3,4]. These devices can wirelessly interface with mobile devices and manufacturer-established websites that allow users to monitor/track their physical activity in real-time, thereby enabling them to receive a steady stream of feedback on their activity and share their data with others (e.g., health care practitioners) who may support them reach their goals.

Recent studies have reported that adherent use of digital health trackers is associated with weight loss and improved medication adherence [5,6], and physicians have noted how useful monitoring of behaviors between clinic visits could be in a health care setting [7]. However, market reports have described high rates of disengagement among users, with over a third stopping use in the first 6 months [8]. Reasons for this high attrition rate are unknown, but, critically, health behaviors are unlikely to be affected if PAMs are not worn for a sustained length of time.

Thus, it is prudent to gain a better understanding of the factors that may promote sustained PAM use over an extended period of time. This will facilitate greater use of this technology in two ways: either supporting broader use of this technology among populations found to have greater adherence or identifying modifiable factors that can drive more tailored intervention design. Survey questions were chosen to allow for the creation of a comprehensive picture of PAM users: their sociodemographic and health characteristics; their reasons for exercising and for using a PAM; and the way in which they interacted with the device. Furthermore, certain questions (e.g., why did you decide to use a PAM?)

were created to explore behaviors associated with physical activity change, such as self-monitoring or social comparison [9,10]. The purpose of this study was to explore which of these factors, including user characteristics and manner of device use, were associated with sustained device engagement in a longitudinal survey of self-selecting PAM users.

METHODS

Study sample

Participants were PAM users living in the USA, recruited via internet-based resources including social media platforms (i.e., Facebook and Twitter), online classifieds (Craigslist), and online message boards. Participants were invited to respond to a series of two online surveys that queried participants about how they used their PAM, as well as sociodemographics and physical activity levels. To ensure a wide distribution across all states, monthly postings were made on local Craigslist sites for the 50 largest metro areas (identified by the U.S. Census Bureau) and the largest city in any other state that did not contain one of the included metro areas. Participants completed the initial survey between November 2015 and December 2016, and those who agreed to be part of a follow-up were contacted via email between September and October 2017 and invited to complete a second online survey. A minimum of 6 months between baseline and follow-up was required based on market reports that show high rates of PAM disengagement among users within the first 6 months [8]). The SurveyMonkey platform was used for data collection.

Inclusion criteria for the initial survey were being ≥18 years, a resident of the USA, and a current or former user of a PAM. At the baseline survey, a total of 1,164 respondents (out of 2,002) reported being current PAM users with the intention to continue use and were invited via email to complete a follow-up survey. After excluding nonrespondents (n = 681) and those who did not fully complete the follow-up survey (n = 65), a total of 418 participants were included in the final analytic sample. All completing the survey(s) were entered into a lottery to win a $100 gift card, with the probability of winning set at ≥1 in 500. The study, including the lottery incentive, was approved by the Institutional Review Board (IRB) at Columbia University. All participants provided informed consent. Information about the IRB-approved study protocol, consent form, and other study materials are publicly available at https://osf.io/ckef8/.

Measures

PAM engagement

At the initial and follow-up surveys, PAM use was ascertained using the question, "Do you currently use an activity monitor?" with yes/no response items. Sustained PAM engagement was defined as those who reported use at the initial and follow-up surveys.

Potential factors associated with sustained PAM engagement

Participants self-reported number of medical conditions, perceived general health, preferred type of exercise, and device-use characteristics (self-purchase vs. gift, data sharing, PAM use in their social network, influence of PAM on activity, and reasons for using the device) were all examined as factors associated with sustained PAM engagement. Preferred mode of exercise was queried to determine whether certain activities (e.g., walking or running) were more prevalent in those who sustained activity monitor use. Reason(s) for device use was queried with response options of yes or no for the following items: (a) "Because I am interested in this type of technology"; (b)"Because I like to monitor my health-related variables"; (c) "To help me lose weight"; (d) "To help me train for a sporting event"; (e) "Because I like the gaming aspect of competing with others"; (f) "Because my friends/family recommended I get one"; (g) "Because my personal trainer or sports coach suggested I get one"; (h) "Because my doctor suggested I get one"; or (i) "Other" (open ended). For the present analysis, answers were compressed, with responses combined for (d)/(e) (e.g., for gaming/competition/training) and for (f)/(g)/(h) (e.g., recommended by family/coach/doctor). With whom participants shared their data with was assessed with the following response items: publicly on social media, privately with friends/family, with doctor/healthcare provider, with coach/personal trainer, or with no one else. Because not sharing data with anyone is a distinct group, responses to this item was recoded as a three-level categorical variable such that coefficients compared a given type of sharing versus not sharing data at all (reference category), accounting for all other types of data sharing. All measures were assessed during the initial survey. See Supplementary Material for further detail.

Covariates

Covariates included age, sex, race, ethnicity, body mass index, relationship status, education, income, length of PAM use prior to baseline, and moderate- to vigorous-intensity physical activity (MVPA) (assessed using Godin–Shephard Leisure Time Questionnaire) [11].

Statistical analysis

A series of logistic regression analyses were conducted to identify factors associated with sustained PAM use. Crude (unadjusted) ORs were initially calculated for each individual variable (e.g., one model tested the association between running as a preferred exercise with sustained PAM use and another tested the association between weight lifting and PAM use). Next, each of these models was adjusted for selected covariates (Model 1). A final model (Model 2) included all covariates and factors associated with sustained device use with a $p \leq .10$ in Model 1 simultaneously. All analyses were conducted using SPSS Statistics 25.0 software (IBM Corp., Armonk, NY).

RESULTS

The median time between completion of the baseline and follow-up surveys was 15.5 (±3.7) months. Of the 418 participants in the analytic sample, 72.5% had sustained use of their PAM. Table 1 presents participant characteristics overall and by PAM use at follow-up (sustained use or discontinued use). The factors associated with sustained PAM use are shown in Table 2. In the final, fully adjusted model, the following variables were significantly associated with sustained use: older age, Hispanic ethnicity, sharing of PAM data via social media (vs. not sharing PAM data, accounting for other types of data sharing), having running as a preferred mode of exercising, and wanting to monitor health variables as a reason for using a PAM.

DISCUSSION

In a prospective survey of self-selecting PAM users, the factors associated with sustained PAM use ~1.3 years later were older age, Hispanic ethnicity, reporting running as a preferred exercise mode, wanting to monitor health variables as a reason for using a PAM, and sharing of device data on social media. When deliberating which populations may respond best to interventions with a goal of sustained PAM use, researchers should consider these factors. The most potentially modifiable factor that emerged was data sharing via social media, and this may represent a possible target for interventions to promote sustained PAM use.

To reap the benefits of the proliferation of PAMs in society, with increasing embeddedness in health care systems [12], a greater understanding of sustained use is a requisite. To our knowledge, the present study is the first to examine factors linked to sustained PAM use among self-selecting users, an underresearched group who can provide unique insights on how PAMs are employed outside of a research setting. Older users and those of Hispanic ethnicity were more likely to sustain use at follow-up, but reasons for these findings are unclear. Interestingly, those who had a preference for running as their mode of exercise were also more likely to have sustained use at follow-up, while those who had a preference for walking/hiking were not. This may suggest that the various features of these devices (heart rate monitoring, GPS tracking, data storage, etc.) may be of more interest to runners than walkers/hikers. The most widely endorsed reason for getting a PAM was a desire to monitor health variables, and this was also significantly associated with sustained use. This finding parallels earlier research, which has found that tracking personal health variables is increasingly important to Americans and associated with improved adherence to health behaviors [6,13].

Of note, how people shared the data from their PAMs was significantly associated with sustained use. However, only sharing publicly on social media was associated with sustained use; other forms of sharing were not. Prior evidence suggests social media platforms may be conducive to augmenting health behavior interventions because they possess a number of useful features (e.g., displaying data to others in real time) that ultimately serve to enhance social support and reinforcement, well-established tenets of behavior change models [14]. It may also be that public sharing is used to increase accountability or that the social interactions that occur as a result of sharing PAM data elicit an intangible social reward [15]. A recent study found that being engaged in an online community can support weight loss [16], while another reported that certain social media platforms may be a more supportive environment than direct contact with family/friends for some people [17]. Strategic use of social media may have the potential to support sustained PAM use in physical activity interventions.

Our study has several limitations. The observational survey nature of our study precludes us from establishing causality; thus, caution is warranted with interpreting our findings. Second, as a sample survey, our study was subject to nonresponse bias, and the rate of response to follow-up was relatively low (35.8%) between the initial baseline and follow-up, which may have impacted results. Nonresponders at follow-up notably differed across a number of sociodemographic and use characteristics (Supplementary Table 1), including gender, race/ethnicity, income, education, MVPA, months of device use, and exercise preference. The low response rate, in part, could have been influenced by the lottery effect. Third, data were self-reported and may be subject to social desirability bias. Fourth, sustained PAM engagement was ascertained with a single-item question ("Do you currently use an activity monitor?") that did not include a time frame (e.g., last week, last month, etc.) or frequency (e.g., times per week). Thus, there is a likelihood of reporting inaccuracies as we relied on the participant's interpretation of current PAM use. Fifth, as social media was one of the modes used to recruit participants, it is possible that those included in this study use social media in a manner different from other PAM users. As such, our finding that sharing of PAM data via social media was associated with sustained PAM use should be interpreted with some caution. Finally, the exact manner (e.g., Facebook vs. Twitter) or volume of

Table 1 | Participant characteristics at baseline: overall and stratified by activity monitor use status at follow-up

	Activity monitor use status at follow-up					
	Overall (n = 418)		Stopped use (n = 115)		Sustained use (n = 303)	
Variable	Mean or n	SD or %	Mean or n	SD or %	Mean or n	SD or %
Sociodemographics						
Age (years)	35.0	±12.5	33.1	±11.3	35.7	±12.9
Female	326	78.0	92	80.0	234	77.2
Race/ethnicity						
Non-Hispanic White	281	67.2	78	67.8	203	67.0
Non-Hispanic Black	34	8.1	11	9.6	23	7.6
Non-Hispanic Asian	47	11.2	16	13.9	31	10.2
Hispanic	41	9.8	4	3.5	37	12.2
Other	15	3.6	6	5.2	9	3.0
Income (<$50,000)	147	35.2	41	35.7	106	35.0
Education (≥bachelors)	301	72.0	90	78.3	211	69.6
Relationship status (partnered)	224	53.6	63	54.8	161	53.1
Health-related measures						
Body mass index	27.3	±6.6	27.2	±5.7	27.3	±6.9
Number of medical conditions						
None	206	49.3	63	54.8	143	47.2
One	132	31.6	31	27.0	101	33.3
Multiple	80	19.1	21	18.3	59	19.5
Perceived health						
Fair/poor	39	9.3	11	9.6	28	9.2
Good	146	34.9	44	38.3	102	33.7
Very good/excellent	233	55.7	60	52.2	173	57.1
Physical activity characteristics						
MVPA[a]	36.2	±24.3	33.4	±23.9	37.2	±24.5
Preferred type of exercise[b]						
Lift weights	160	38.3	45	39.1	115	38.0
Walk/hike	309	73.9	80	69.6	229	75.6
Run	194	46.4	46	40.0	148	48.8

(Continued)

Table 1 | Continued

	Activity monitor use status at follow-up					
	Overall (n = 418)		Stopped use (n = 115)		Sustained use (n = 303)	
Variable	Mean or n	SD or %	Mean or n	SD or %	Mean or n	SD or %
Bike	89	21.3	23	20.0	66	21.8
Swim	39	9.3	10	8.7	29	9.6
Dance/Aerobics	95	22.7	21	18.3	74	24.4
Yoga/Pilates	127	30.4	32	27.8	95	31.4
Team sports	25	6.0	7	6.1	18	5.9
Device-use characteristics						
Months of device use	11.4	±11.3	9.6	±10.4	12.1	±11.5
Device source—gift	171	40.9	52	45.2	119	39.3
Data sharing[b]						
On social media	48	11.5	4	3.5	44	14.5
Privately with friends/family	233	55.7	62	53.9	171	56.4
With doctor	38	9.1	7	6.1	31	10.2
With coach/trainer	18	4.3	4	3.5	14	4.6
Other activity monitor users in their network (none)	57	13.6	13	11.3	44	14.5
Perceived influence of device on activity (positive)	326	78.0	90	78.3	236	77.9
Reasons for using an activity monitor[b]						
Interested in the technology	236	56.5	63	54.8	173	57.1
To monitor health variables	305	73.0	79	68.7	226	74.6
To help lose weight	222	53.1	58	50.4	164	54.1
For gaming/competition/training	99	23.7	30	26.1	69	22.8
Recommended by family/coach/doctor	80	19.1	21	18.3	59	19.5

Data presented as mean ± standard deviation (*SD*) or frequencies and percent.
[a]Godin Leisure Time Physical Activity Questionnaire—Moderate and Strenuous section.
[b]Respondents had the option to choose more than one answer.

Table 2 | Factors associated with sustained physical activity monitor use

	Unadjusted model[a]		Model 1[b]		Model 2[c]	
Variables	OR (95% CI)	*p*-value	OR (95% CI)	*p*-value	OR (95% CI)	*p*-value
Sociodemographics						
Age (years)	1.02 (1.00–1.04)	.056	1.02 (1.00–1.04)	.066	1.03 (1.01–1.05)	.014
Female	0.85 (0.50–1.44)	.542	0.93 (0.53–1.63)	.790	0.99 (0.56–1.78)	.983
Race/ethnicity						
Non-Hispanic White	1.00 (Ref)		1.00 (Ref)		1.00 (Ref)	
Non-Hispanic Black	0.80 (0.37–1.73)	.575	0.78 (0.35–1.74)	.547	0.56 (0.24–1.31)	.183
Non-Hispanic Asian	0.74 (0.39–1.44)	.379	0.83 (0.42–1.64)	.593	0.83 (0.41–1.68)	.612
Hispanic	3.55 (1.23–10.30)	.020	3.44 (1.17–10.16)	.025	3.67 (1.20–11.26)	.023
Other	0.58 (0.20–1.67)	.311	0.67 (0.23–1.99)	.472	0.52 (0.17–1.59)	.249
Income (<$50,000)	0.97 (0.62–1.52)	.898	1.04 (0.64–1.69)	.887	0.98 (0.59–1.61)	.924
Education (≥bachelors)	0.64 (0.38–1.06)	.081	0.65 (0.38–1.12)	.119	0.69 (0.40–1.20)	.190
Relationship status (partnered)	0.94 (0.61–1.44)	.763	0.78 (0.49–1.24)	.296	0.68 (0.42–1.10)	.118
Health-related measures						
BMI	1.00 (0.97–1.04)	.875	1.00 (0.96–1.03)	.773	1.01 (0.97–1.05)	.807
Number of Medical Conditions						
None	1.00 (Ref)		1.00 (Ref)			
One	1.44 (0.87–2.37)	.156	1.32 (0.79–2.22)	.289		
Multiple	1.24 (0.69–2.21)	.471	1.11 (0.59–2.07)	.755		
Perceived health						
Fair/poor	1.00 (Ref)		1.00 (Ref)			
Good	0.91 (0.42–1.99)	.815	1.05 (0.45–2.47)	.911		
Very good/ excellent	1.13 (0.53–2.41)	.747	1.18 (0.48–2.92)	.722		
Physical activity characteristics						
MVPA	1.01 (1.00–1.02)	.149	1.01 (1.00–1.02)	.190	1.00 (0.99–1.01)	.834
Preferred type of exercise[d]						
Lift weights	0.95 (0.61–1.48)	.825	0.88 (0.55–1.43)	.614		
Walk/hike	1.35 (0.84–2.18)	.212	1.24 (0.74–2.09)	.410		
Run	1.43 (0.93–2.22)	.106	1.61 (0.93–2.79)	.092	1.82 (1.02–3.24)	.043
Bike	1.11 (0.65–1.90)	.691	1.10 (0.63–1.93)	.735		

(Continued)

Table 2 | Continued

Variables	Unadjusted model[a] OR (95% CI)	Unadjusted model[a] *p*-value	Model 1[b] OR (95% CI)	Model 1[b] *p*-value	Model 2[c] OR (95% CI)	Model 2[c] *p*-value
Swim	1.11 (0.52–2.36)	.784	1.04 (0.48–2.25)	.923		
Dance/aerobics	1.45 (0.84–2.48)	.181	1.61 (0.91–2.86)	.100		
Yoga/pilates	1.19 (0.74–1.90)	.484	1.17 (0.71–1.92)	.541		
Team sports	0.97 (0.40–2.40)	.955	0.75 (0.28–2.00)	.568		
Device-use characteristics						
Months of device use	1.02 (1.00–1.05)	.043	1.02 (1.00–1.05)	.057	1.02 (1.00–1.05)	.062
Device source—gift	0.78 (0.51–1.21)	.27	0.86 (0.55–1.34)	.493		
Data sharing[e]						
On social media	5.12 (1.74–15.08)	.003	4.94 (1.65–14.82)	.004	5.11 (1.64–15.93)	.005
Privately with friends/family	1.28 (0.82–2.02)	.279	1.36 (0.84–2.20)	.209		
With doctor	2.06 (0.85–5.02)	.111	1.78 (0.71–4.42)	.217		
With coach/trainer	1.63 (0.51–5.22)	.411	1.27 (0.38–4.24)	.697		
Other activity monitor users in their network (none)	1.33 (0.69–2.58)	.393	1.09 (0.54–2.21)	.806		
Perceived influence of device on activity (positive)	0.98 (0.58–1.65)	.934	0.96 (0.56–1.64)	.880		
Reasons for using an activity monitor[d]						
Interested in the technology	1.01 (0.71–1.69)	.67	1.11 (0.77–1.94)	.394		
To monitor health variables	1.34 (0.84–2.14)	.227	1.55 (0.94–2.55)	.089	1.73 (1.02–2.92)	.042
To help lose weight	1.16 (0.75–1.78)	.5	1.31 (0.81–2.13)	.274		
For gaming/competition/training	0.84 (0.51–1.37)	.477	0.88 (0.52–1.48)	.618		
Recommended by family/coach/doctor	1.08 (0.62–1.88)	.779	1.06 (0.60–1.52)	.853		

Bold = $p < .05$.
BMI, body mass index.
[a]All variables examined individually.
[b]Adjusted for covariates (age, sex, race/ethnicity, BMI, relationship status, education, income, MVPA, and length of use prior to baseline).
[c]Adjustment for covariates, plus all variables with $p \leq .10$ in Model 1.
[d]Tested as individual dummy codes (e.g., preferred lifting weights vs. all other types).
[e]Tested as a three-level categorical variable such that coefficients compare a given type of sharing versus not sharing data at all (reference category), accounting for all other types of data sharing.

social media sharing was not assessed, so whether a particular level of sharing is needed for sustained engagement is unknown.

In conclusion, the most notable finding of our prospective survey of self-selecting PAM users was that those who shared data from their device publicly on social media were more likely to sustain device use at follow-up. Future studies should elucidate features of social media that might increase the engagement and retention of PAM users. Nonetheless, results of the current study suggest that encouraging users to share their data publicly may be a potential strategy to promote longer PAM engagement.

SUPPLEMENTARY MATERIAL

Supplementary material is available at *Translational Behavioral Medicine* online.

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Compliance with Ethical Standards

Conflicts of Interest: The authors of this paper declare that they have no conflicts of interest.

Authors' Contributions

C.P.F. conceptualized and designed the study, and collected data. C.P.F. and K.M.D. conceptualized and designed the analysis, drafted the initial manuscript, and reviewed and revised the manuscript. T.C. conceptualized and designed the data analysis, and critically reviewed and revised the manuscript.

Ethical Approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This article does not contain any studies with animals performed by any of the authors.

Informed Consent: Informed consent was obtained from all individual participants included in the study.

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