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Perceived vs. observed mHealth behavior: A naturalistic investigation of tracking apps and daily movement

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Abstract

Research on mHealth apps provides mixed evidence regarding their effectiveness for behavior change, including physical activity. Synthesizing prior perspectives, we test predictors of tracking app and physical activity intentions (Study 1; $n = 658$) and their links to everyday mobility (Study 2; $n = 418$; $n = 27{,}617{,}440$ observations). Study 1 showed that individuals have overlapping perceptions of tracking apps and physical activity. Taking a naturalistic mobile sensing approach, Study 2 found that tracking app and physical activity intentions predicted self-reported physical activity – but not logged movement (i.e., walking, cycling, or running). Tracking app use was not related to the level of logged movement in daily life. However, participants who regularly used tracking apps were more likely to view them as impactful, suggesting that daily mHealth app use is related to perceived (vs. observed) behavior change. Together, our studies illuminate how perceptions of mobility and mobile media – and their effects – can become intertwined in users' minds.

Keywords

Technology acceptance model, theory of planned behavior, health apps, fitness apps, mobile sensing, perception gap, presumed effects

Our media behaviors are now deeply synced with our daily mobility patterns (Pawlak, 2020; Ross et al., 2022; Singleton, 2019; von Pape, 2020;). By allowing users to record and reflect on their movement (or "steps") with just a few swipes, mHealth apps streamline the process of tracking and self-evaluating our physical activity via daily movement. Over half of smartphone users have downloaded a fitness or health-related app (Krebs & Duncan, 2015). Yet, despite massive growth in personal health technologies (McKay et al., 2018), physical activity levels in the U.S. remain suboptimal (National Center for Health Statistics, 2018). Currently, just 1 in 4 adults gets the recommended 150 min of physical activity each week (Centers for Disease Control and Prevention, 2020a, 2020b; National Center for Health Statistics, 2018).

We present two studies that seek to clarify how tracking apps—that is, apps that are designed to track movement or steps using global positioning system (GPS) or other technology—are related to intended and real-world behavior. Some studies have shown tracking apps to affect physical activity, but the detected effects are often small (see reviews: Byambasuren et al., 2018; Hall et al., 2015). Furthermore, current approaches to studying mHealth technologies typically examine just *one* app at a time. Studies focusing on single apps may fail to capture a complete picture of how people are using them (Pawlak, 2020). A more naturalistic and holistic exploration of movement tracking apps is thus needed, including careful testing of the impacts of these apps on behaviors and factors driving behavior change (McCallum et al., 2018). Guided by the theory of planned behavior (TPB; Ajzen, 1991) and technology acceptance model (TAM; Davis, 1989), we examine relationships between tracking app and physical activity perceptions (Study 1), along with their links to real-world app use and movement (Study 2). Importantly, our studies were not designed to test the causal relationships between tracking app use and physical activity. Rather, given the increasingly interwoven nature of smartphone usage and daily movement, we sought to examine how perceptions of tracking apps and physical activity relate to one another—and whether these perceptions map onto observed mHealth behavior in daily life.

Study 1

Despite the interwoven nature of mHealth app use within everyday life (Lomborg et al., 2018), theorizing regarding daily mHealth and mobility has largely remained separate. In response to this literature gap, we aimed to build on TPB and TAM predictions to explain how tracking app use relates to daily movement (Figure 1). The TPB (Fishbein & Ajzen, 2010) proposes that intentions (and subsequent behaviors) are the product of attitudes, norms, and perceived behavioral control (e.g., one's perceived capacity to perform a behavior). Similarly, the TAM proposes that technology use intentions (and subsequent behaviors) are shaped by attitudes towards the technology, perceived usefulness (the degree to which a technology will enhance performance), and ease of use (the degree to which technology use will be free of effort; Davis, 1989). A norms variable was later added to the model (i.e., TAM2; Venkatesh & Davis, 2000), which referred to individuals' perceptions of what important others think about a given technology behavior. Numerous studies have shown TPB variables predict intentions to engage in physical activity (e.g., Armitage, 2005; Courneya, 1995; Dzewaltowski et al., 1990; Hamilton

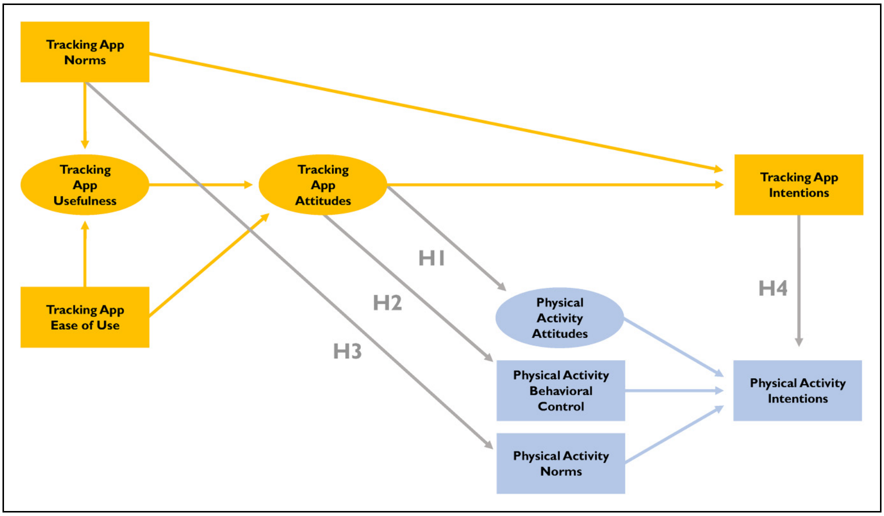

Figure 1. Study 1 conceptual model.
Note. Diagram displaying the Study 1 conceptual model and specifying novel hypotheses. Yellow denotes key constructs and proposed relationships from the technology acceptance model (Venkatesh & Davis, 2000). Blue denotes key constructs and proposed relationships from the theory of planned behavior (Ajzen, 1991). The model hypotheses for Study 1 are displayed in grey.

& White, 2008), and the original TAM has been shown to predict intentions to use a fitness app (Beldad & Hegner, 2018).

In addition to testing the main predictions of both models, Study 1 set out to explore associations between key TAM and TPB constructs. First, we proposed that attitudes towards tracking apps will be positively associated with attitudes towards physical activities (H1). Prior perspectives suggest that individuals with stronger attitudes are more likely to have attitude-consistent beliefs and cognitions (Chaiken et al., 2014). In other words, attitudes towards physical activity and tracking technologies may mutually reinforce each other given their shared focus on physical health. Indeed, the majority of participants in a recent study strongly agreed that using apps increased desire, frequency, and consistency of physical activity (Hoj et al., 2017). Second, we anticipated that holding more positive attitudes towards tracking apps would be associated with perceived behavioral control (PBC) related to physical activities (H2). As noted by Ajzen (2002), the more favorable our attitudes are towards something, the greater our perceived behavioral control is likely to be. In the Hoj et al. (2017) study noted above, over 80% of participants agreed that apps influenced their ability to be physically active and to achieve their activity-related goals. Thus, those who view tracking apps as worthwhile and useful may perceive greater control over their ability to engage in physical activity.

Third, we hypothesized that perceived descriptive norms (i.e., beliefs about the extent to which others are doing something; Cialdini et al., 1990) for tracking app use and physical activities would be positively associated (H3). Tracking apps are designed for self-surveillance to record and encourage movement (Zheng, 2021). If we perceive that others are using tracking apps, we are likely to perceive they are also engaging in physical activity. We focus on descriptive norms (vs. injunctive norms) given that descriptive norms have been associated with technology and internet use in prior work (Cho, 2011; Sumaedi & Sumardjo, 2020), as well as exercise intentions and behaviors (Cho & Tian, 2021). Finally, we proposed that intentions to use tracking apps would be positively associated with intentions to engage in physical activity (H4). See Figure 1. Although physical activity encompasses a wider variety of activities than those tracked by many mHealth apps, people who are motivated to use apps are likely doing so to increase their overall physical activity. This last hypothesis echoes past research showing that fitness app users (vs. non-users) are more physically active (Barkley et al., 2020) and more likely to maintain physical activity over time (Wang et al., 2016).

Method

Study 1 analyzed baseline data from Project mCog: a multi-study project assessing naturalistic smartphone use in combination with daily mobility. All study procedures were approved by the Institutional Review Board (IRB) at the corresponding author's institution. From May to December 2019, 2,748 participants completed a pre-screening survey after being recruited via: (a) a random sample of university students via email; or (b) local Facebook or Instagram ads targeted within 25 miles of the city center. Of those, 879 participants met the eligibility criteria and approximately 75% ($n = 658$) completed the baseline survey. To be eligible, participants were required to own an Android smartphone capable of running the study app (see Study 2). The average age of participants was

35.33 years (SD = 12.02; range = 18–76 years) and 65% (n = 430) were female. Additional information about the recruitment process and sample characteristics are provided in the online supplementary materials (OSM).[1]

Measures. All self-report measures for Study 1, as well as other measures collected as part of the overall project (Project mCog), are available on the project information page on Open Science Framework (OSF).[2] All items in Study 1 were measured on a 5-point Likert scale from 1 (*strongly disagree*) to 5 (*strongly agree*), unless noted below.

Theory of planned behavior. TPB measures were based on Ajzen (1991, 2003). *Perceived behavioral control* was measured with two items (e.g., "I have control over whether I can take part in physical activities; r = .70). *Attitudes* were measured using four five-point semantic differential pairs: not enjoyable to enjoyable; unpleasant to pleasant; harmful to beneficial; not useful to useful (Cronbach's α = .80). *Descriptive norms* were measured with a single item: "My family/friends participate in physical activities." Finally, *physical activity intentions* were measured by asking participants: (a) the number of days they planned to engage in physical activity (e.g., "running, walking for exercise, calisthenics, golf, or gardening") on a scale from 0 to 14 days; and (b) the planned duration of physical activity on those days with responses ranging from 1 (*less than 15 min*) to 5 (*more than 60 min*). Physical activity days and duration were multiplied to estimate the number of 15-min intervals of intended activity during the 14-day study period (*range* = 0–70). *Baseline physical activity* was assessed with response options ranging from 0 (*0 times per week*) to 8 (*more than 7 times per week*).

Technology acceptance model. Items measuring TAM constructs were modified from Davis (1989) unless noted and designed to mirror TPB measures. *Perceived usefulness* was measured with three questions, including "I find tracking apps useful" (Cronbach's α = .88). *Attitudes towards tracking apps* were measured with three five-point semantic differential pairs: not enjoyable to enjoyable; unpleasant to pleasant; harmful to beneficial (Cronbach's α = .85). Perceived *ease of use* was measured with a single item ("I find tracking apps easy to use"). Likewise, *descriptive norms* (Ajzen, 2003) were measured by a single item: "My family/friends use tracking apps." *Tracking app use intentions* were measured with the item "Over the next 2 weeks, how many days do you plan on using apps that track your movement or steps do you plan to regularly use?" (with response options from 0 to 14 days). *Baseline tracking app usage* also was assessed with response options ranging from 1 (*2 or more times a day*) to 5 (*less than once a month*).

Data analysis. Descriptive statistics and zero-order correlations were first conducted to understand distributions and patterns in the data (Table 1). Confirmatory factor analysis was used to assess the robustness of multi-item scales. A structural equation model was specified to test our proposed hypotheses. Due to non-normality, models were tested using the *lavaan* package in R 4.0.2 with diagonally weighted least squares estimator (DWLS; Rosseel et al., 2020). All models used listwise deletion for missing values. In the case of non-normal, ordinal variables, DWLS is less biased and more consistent

Table 1. Study 1 descriptive statistics and Pearson correlations between variables.

	M	*SD*	2.	3.	4.	5.	6.	7.	8.	9.
1. Tracking app usefulness	3.84	0.83	.57***	.58***	.37***	.40***	.11**	.17***	.14***	.09*
2. Tracking app ease of use	4.03	0.86		.45***	.27***	.39***	.10*	.19***	.14***	.07
3. Tracking app attitudes	3.83	0.94			.24***	.29***	.07	.45***	.09*	.10**
4. Tracking app norms	3.69	1.09				.15***	.35***	.04	.03	.02
5. Tracking app intentions	6.49	5.95					.04	.13**	.08	.23***
6. Physical activity norms	3.78	1.01						.20***	.25***	.16***
7. Physical activity attitudes	4.17	0.80							.31***	.33***
8. Physical activity PBC	4.38	0.74								.25***
9. Physical activity intentions	18.37	15.22								

Note. $n = 658$.
*$p \leq .05$, **$p < .01$, ***$p < .001$.
PBC: perceived behavioral control.

than maximum likelihood estimation while making no distributional assumptions about observed variables (Beauducel & Herzberg, 2006; Li, 2016). Model fit was assessed using the comparative fit index (CFI; values $\geq$ 0.95), standardized root mean square residual (SRMR; values $\leq$ 0.8), root mean square error of approximation (RSMEA; values $\leq$ 0.06), and Chi-square test of model fit (χ^2) for DWLS (Zhao, 2015). The full structural model controlled for baseline tracking app use and physical activity.

Results

We first conducted a confirmatory factor analysis (CFA) to assess the dimensionality of the three multi-item scales assessed on the baseline survey: perceived usefulness of tracking apps, attitudes toward tracking apps, and attitudes toward physical activity. The model fit was acceptable (χ^2 (32) = 96.68, p < .001, CFI = .979, RMSEA = .06, SRMR = .08) with standardized item loadings above .62 for all three scales.

To test study hypotheses, the full structural model was tested. Model fit indices suggested an acceptable fit to the data (χ^2 (122) = 411.48, p < .001, CFI = .92, RMSEA = .07, SRMR = .09). See Figure 2 for standardized path coefficients.

The original TAM predictions were largely supported. Tracking app usefulness was positively associated with tracking app norms, β = .14, p = .011, as well as tracking app ease of use, β = .69, p < .001. In addition, tracking app usefulness was positively related to tracking app attitudes, β = .37, p < .001, which were positively related to intended tracking app use, β = .12, p = .003. However, no relationship was detected between tracking app norms and intentions. Likewise, original TPB predictions were largely supported. Physical activity attitudes, β = .29, p < .001, and perceived behavioral

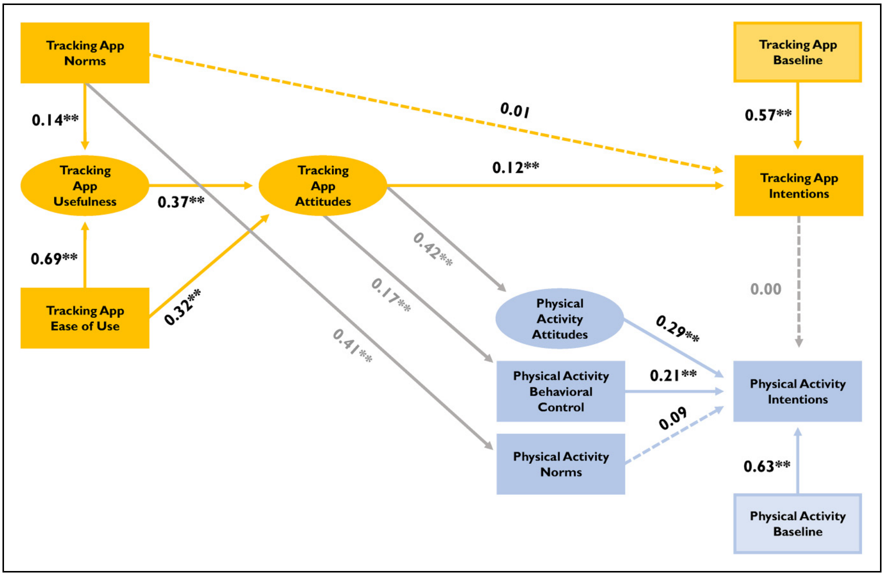

Figure 2. Full Structural Model with Standardized Parameter Estimates.
Note. $n = 658$. Model χ^2 (122) = 414.48, $p < .001$, comparative fit index (CFI) = .92, root mean square error of approximation (RMSEA) = .07, standardized root mean square residual (SRMR) = .09. Dashed lines indicate statistically insignificant results. $^{*}p \leq .05$; $^{**}p < .01$.

control, $\beta = .21$, $p < .001$, were positively associated with physical activity intentions. The relationship between physical activity norms and intentions was marginally significant by conventional standards, $\beta = .09$, $p = .061$.

Beyond core TPB and TAM predictions, our data showed that attitudes towards tracking apps were positively associated with attitudes towards physical activity, $\beta = .41$, $p < .001$ (H1 supported). Tracking app attitudes were positively related to perceived behavioral control of physical activity, $\beta = .17$, $p < .001$ (H2 supported). Tracking app norms were positively associated with physical activity norms, $\beta = .42$, $p < .001$ (H3 supported). However, tracking app intentions were unrelated to physical activity intentions in our model specification (H4 unsupported), despite being positively related as a zero-order correlation (see Figure 2).

Discussion

Study 1 generally provided support for core predictions within the TPB and TAM. However, perceived norms were less influential on both tracking app and physical activity intentions in our study. Although TPB studies have generally supported the norms-intention relationship in the context of physical activity, TAM studies have often not (Ketikidis et al., 2012, Yuan et al., 2015). Because health and fitness apps are among those most often used (Lobelo et al., 2016), others' use of physical activity tracking apps may have less influence on personal intentions. Indeed, some research has shown that peers do not impact exercise behaviors, with or without apps (Herrmann & Kim, 2017).

Our analyses illustrated the interwoven nature of mobile media and personal health. In particular, those who held more positive attitudes towards tracking apps also had more positive attitudes towards physical activity, as well as greater perceived behavioral control of their physical activity. These findings point to the possibility that technology-related perceptions could indirectly impact health-related perceptions. In addition, our data displayed a relationship between descriptive norms for tracking app use and physical activity; that is, the more participants perceived others to be using tracking apps, the more they perceived them to be engaging in physical activity. Altogether, the results affirm how perceptions of mHealth tracking apps and actual health behavior may coalesce in users' minds.

Finally, the fact that we did not detect a significant relationship between tracking app and physical activity intentions in the structural model was unexpected. This may be due to the fact that attitudes and perceived behavioral control accounted for a substantial proportion of the variance in intended physical activity, leaving little variance to be explained by intended tracking app use (or even physical activity norms). Indeed, when examining the bivariate correlations, we observed a positive small association ($r = .23$) between tracking app and physical activity intentions. We next turn to Study 2 to shed light on the real-world links between tracking apps and daily movement, while also considering the *perceived impact* of mHealth apps.

Study 2

Beyond intentions, understanding the perceptual factors that drive everyday use of mHealth apps and engagement in key types of physical activity is crucial for the development of health technologies and interventions. Study 2 draws on self-reported and recorded app use and daily movement to investigate intention–behavior relationships proposed by the TPB and TAM (H1–H2), as well as to probe the real-world relationships between tracking apps and daily movement (H3–H4). Our measurement approach thus centers on physical movement through everyday spaces (i.e., walking, biking, running), rather than stationary exercises (e.g., spin classes). Altogether, our Study 2 data allow for a naturalistic and ecologically valid investigation of tracking app usage to unearth how tracking and mobility are synced in daily life.

In alignment with the TAM (Davis, 1989), we expected that intentions to use tracking apps would predict logged (H1a) and self-reported (H1b) tracking app use. Likewise in accordance with the TPB (Fishbein & Ajzen, 1975), we expected that physical activity intentions would predict logged movement (H2a) and self-reported physical activity (H2b). Though recorded movement does not account for all forms of physical activity, it represents a central component and reflection of everyday health behavior. The intention–behavior relationship is supported in the context of physical activity, although it is not particularly strong (McEachan et al., 2011; Rhodes & Dickau, 2012). Notably, mobile media—and tracking apps on smartphones, in particular—may help strengthen the link between intention and behavior. Personal phones are deeply linked to individuals' everyday habits and even identities (Ross & Bayer, 2021), which contribute to their potential to monitor and improve health (Michie et al., 2017).

Moreover, by allowing users to record and reflect upon their movement, tracking apps may also bolster physical activity above and beyond intentions. Thus, we hypothesized that those who use tracking apps more frequently will engage in more daily movement (H3) over the 2-week study period, controlling for intentions and past behavior. At the same time, some research has shown that fitness trackers that record movement are "unlikely to generate meaningful changes in physical activity behaviors" (Lynch et al., 2020, p. 428). Other work has noted small effects of tracking app use on physical activity behavior (see reviews: Byambasuren et al., 2018; Hall et al., 2015), while also noting the low quality of evidence. As described in Lynch et al. (2020), measurement of physical activity varies significantly across studies. Some studies incorporate objective measures while others rely on self-reports, making the generalization of findings across studies difficult. Here, by examining both, we pursue a more comprehensive approach to understand the role of daily movement specifically.

However, there is often a meaningful gap between actual and self-reported data in regard to physical activity and tracking apps (as well as mobile communication at large; Boase & Ling, 2013; Vanden Abeele et al., 2013). That is, what people *believe* they are doing does not match what they are *actually* doing. The observed-versus-perceived gap has been studied in relation to the TPB more broadly, with TPB variables shown to better predict self-report than behavioral measures (McEachan et al., 2011). This disparity between perceived and observed behavior may be driven by self-evaluation inflation or deflation (Scholer et al., 2014). Independent of changes in daily activity, people who use tracking apps may believe that apps are contributing to their health goals. Therefore, we expected that those who engage with tracking apps more will hold stronger beliefs that their app use *impacted* their level of physical activity (H4).

Method

At the end of the baseline survey (Study 1), participants were provided with a link to download the study application, which was custom-made for Project mCog. The study app passively recorded their use of other apps and logged their movement over the next 2 weeks, transmitting data up to every 10 s regarding tracking app usage (e.g., MyFitnessPal), location (i.e., GPS), and mobility/transportation status (via the Google application programming interface [API]) to a secure server. See Figure 3 for an illustration of the logged data collected via the study app.

At the end of this 14-day period, participants completed an endpoint survey, which inquired about their app usage and physical activity over the previous 2 weeks. Of the 658 participants who took part in the baseline survey, 71% (n = 465) downloaded the app, contributed logs of their phone and movement activities (n = 28,752,369 device observations), and completed the endpoint survey. Of those, we excluded those who completed the endpoint survey over a week after completing the 2-week tracking period (n = 16) or experienced difficulties with data transmission (n = 31) (see the OSM for more information), leaving a final sample of 418 participants and 27,617,440

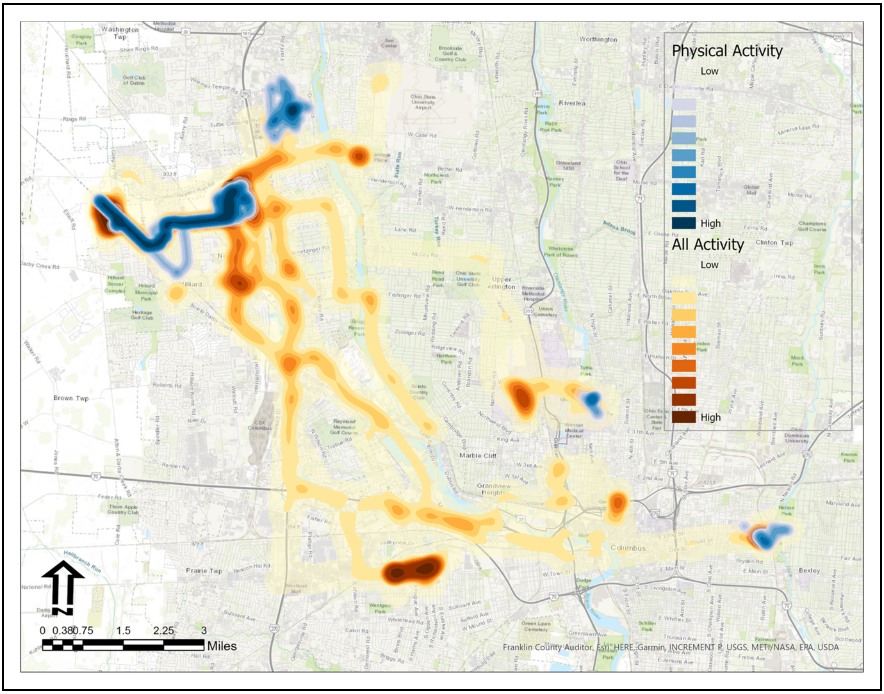

Figure 3. Logged data collected via study application.
Note. Map displaying the logged data collected for one example participant across the 2-week study period by the study application. Logged movement is shown in blue. All other logged data points for the participant (i.e., observations lacking physical activity according to the Google application programming interface (API) are shown in orange. Darker shading indicates a greater amount of logged data points within a geospatial area.

device observations. Of those 418 individuals, about 65% ($n = 271$) were women and the average age was 35.04 years ($SD = 11.26$).

Measures

Logged app use. Logged app use was operationalized as the proportion of days with recorded tracking app use (out of days with any app use during the study period). App use represented any activity during which an app was in the foreground of participants' phones. Forty-three tracking apps were either: (a) regularly used; or (b) self-reported in the endpoint survey (see the OSM for a list of these apps). On average, participants used tracking apps on 34% of study days. Because the logged tracking app use variable was not normally distributed (i.e., bimodal), it was recoded into three ordinal categories (1: no tracking app use; 2: tracking app use logged $\leq$ 80% of study days; 3: tracking app use logged > 80% of study days).

Self-reported tracking app use. Self-reported tracking app use was assessed in the end-point survey. Participants reported how many days they used tracking apps to track their movements or steps during the study period. On average, participants said they used tracking apps 7.68 days during the 14-day study period, or 55% of study days. To align with the logged tracking app use variable, this variable was grouped into three ordinal categories (1: no tracking app use self-reported; 2: tracking app use self-reported $\leq$ 80% of study days; 3: tracking app use self-reported > 80% of study days).

Logged movement. Logged physical activity was operationalized as the amount of time per day that was spent engaging in physical movement during the study period (see Figure 3). To account for differences in data transmission across phones and participants, we divided the logged data period into 15-min intervals. Each movement interval was then coded as a form of physical activity if their modal mobility/transportation status during that time interval (based on the Google API) was biking, walking, or running. Therefore, logged movement was measured as the number of 15-min intervals of physical movement per day.

Self-reported physical activity. Self-reported physical activity was assessed on the end-point survey in the same manner as intended physical activity in Study 1 (with the item wording edited to reference the prior 2-week study period). Specifically, participants were asked: (a) the number of days they participated in physical activity (e.g., "running, walking for exercise, calisthenics, golf, or gardening") on a scale from 0 to 14 days; and (b) the duration of physical activity on those days with responses ranging from 1 (*less than 15 min*) to 5 (*more than 60 min*). Physical activity days and duration were multiplied to estimate the number of 15-min intervals of intended activity during the 14-day study period (*range* = 0–70). To increase the comparability of logged movement with self-reported physical activity, the self-reported measure was converted to minutes per day.

Perceived impact. After self-reporting their tracking app use and physical activity over the 2-week study period, participants were asked to assess the perceived impact of tracking app use on physical activity with the item "To what extent do you think apps that track your movement or steps have impacted your activity level?" The item was measured on a scale from 0 (*no impact*) to 5 (*strong impact*). See the OSM for additional measurement details on all Study 2 measures, including validation and alternative operationalizations.

Data analysis. Descriptive statistics and Spearman correlations for relevant variables are displayed in Table 2. We specified generalized linear models to examine predictors of tracking usage, physical activity, and perceived impact of tracking apps. All models were tested using the MASS package in R and used listwise deletion for missing values. First, ordered logit models were specified to examine the predictors of logged (Model 1A) and self-reported (Model 1B) tracking app use. Second, negative binomial models were specified to examine the predictors of logged movement (Model 2A) and self-reported physical activity (Model 2B), which had negative binomial distributions.

Table 2. Study 2 descriptive statistics and spearman correlations between variables.

	M	*SD*	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. Data transmission days[a]	13.81	0.92	.02	.09	−.01	.04	.02	−.02	−.04	.08	.11*
2. Baseline tracking app use	4.17	1.62		.58***	.43***	.54***	.07	.12*	.05	.08	.45***
3. Tracking app use intentions	6.91	5.92			.39***	.56***	.13**	.19***	.03	.15**	.48***
4. Logged app use	1.78	0.80				.62***	.05	.06	.08	.02	.37***
5. Self-reported tracking app use	1.89	1.16					.09	.09	.05	.05	.51***
6. Baseline physical activity	10.07	8.12						.76***	.27***	.73***	.15**
7. Physical activity intentions	20.08	15.80							.27***	.68***	.20***
8. Logged movement	32.72	34.89								.26***	.07
9. Self-reported physical activity	18.43	16.31									.21***
10. Perceived impact	1.91	1.53									

Note. $n = 417$. [a]Number of days device data was transmitted from participants (range: 0–14).
$^{*}p \leq .05$, $^{**}p < .01$, $^{***}p < .001$.

Finally, ordered logit models were tested to assess perceived impact; separate models were specified for logged app use and movement (Model 3A) and self-reported tracking and physical activity (Model 3B). All models controlled for age, gender, the season when the data were collected, and baseline tracking app use. We also controlled for the number of days that data was transmitted to the study team ("data transmission days") in models that included logged variables. As a robustness check, we ran additional models (i.e., ordinary least squares [OLS], logistic, and rank regressions) using the *Stats* and *Rfit* packages, which revealed largely consistent results with the models reported below (see the OSM).

Results

Intention–behavior relationships. Models 1A and 1B examined intention–behavior relationships for tracking app use (Table 3). Model 1A showed that intended tracking app use was unassociated with logged tracking app use, $\beta = 0.03$, $p = .252$ (H1a not supported). Model 1B specified intended tracking app use as a predictor of self-reported tracking app use, showing tracking app use intentions were associated with greater self-reported tracking app use, $\beta = 0.12$, $p < .001$ (H1b supported).

Models 2A and 2B investigated intention–behavior relationships for physical activity (Table 3). Model 2A showed that physical activity intentions were unassociated with logged movement, $\beta = 0.01$, $p = .123$ (H2a not supported).[3] Model 2B specified intended physical activity as a predictor of self-reported physical activity, revealing that physical activity intentions were associated with greater self-reported physical activity, $\beta = 0.01$, $p = .009$ (H2b supported).

Tracking app use–physical activity relationships. Beyond intentions, Models 2A and 2B examined relationships between tracking app use and physical activity over the 2-week period. Model 2A showed that logged tracking app use was not related to logged movement, $\beta = -0.09$, $p = .243$. Model 2B specified self-reported tracking app use as a predictor of self-reported physical activity, and found that self-reported tracking app use did not predict self-reported physical activity, $\beta = -0.05$, $p = .500$ (H3 was not supported).

Perceived impact. Finally, Models 3A and 3B investigated the relationships between tracking app usage and perceived impact (Table 4). Model 3A specified logged tracking app use as a predictor of perceived impact, and found that logged tracking app use was (marginally) positively associated with perceived impact at conventional significance standards, $\beta = 0.24$, $p = .093$.[4] Model 3B specified self-reported tracking app use as a predictor of perceived impact, and revealed that self-reported tracking app use was positively associated with perceived impact, $\beta = 0.80$, $p < .001$ (H4 partially supported).

General discussion

We adopted an ecological measurement approach to clarify the interrelationships between perceived and observed mHealth behavior. Our studies reinforce foundational frameworks in health behavior, while also providing new perspectives on "media

Table 3. Regression models predicting logged and self-reported tracking app use and physical activity.

	Model 1A			Model 1B			Model 2A			Model 2B		
	Logged app use[a]			Self-reported tracking app use[a]			Logged movement[b]			Self-reported physical activity[b]		
	(n = 414)			(n = 412)			(n = 414)			(n = 411)		
	β	SE	p	β	SE	p	β	SE	p	β	SE	p
Age	<.01	.01	.656	<.01	.01	.872	–.02	<.01	<.001**	< .01	<.01	.265
Gender[c]	–.16	.24	.500	–.58	.27	.033*	–.35	.11	.002**	–.03	.09	.766
Season: Spring[d]	–.22	.37	.542	.06	.41	.887	–.29	.18	.098	.18	.14	.208
Season: Summer[d]	–.25	.25	.319	–.23	.29	.428	.12	.12	.325	.20	.10	.046*
Data transmission days	–.09	.13	.481	–	–	–	.08	.06	.199	–	–	–
Baseline tracking app use	.58	.09	< .001**	.67	.10	<.001**	.05	.04	.232	.04	.04	.238
Intended tracking app use	.03	.13	.252	.12	.02	<.001**	<.01	.01	.914	.01	.01	.352
Logged tracking app use	–	–	–	–	–	–	–.09	.07	.243	–	–	–
Self-reported tracking app use	–	–	–	–	–	–	–	–	–	–.05	.07	.500
Baseline physical activity	–	–	–	–	–	–	.02	.01	.022*	.06	.01	<.001**
Intended physical activity	–	–	–	–	–	–	.01	.01	.123	.01	.004	.009**

Note. [a]Estimated using ordered logit model; [b]Estimated using negative binomial model; [c]Gender reference group: male; [d]Season reference group: autumn.
*$p \leq .05$; **$p < .01$.

Table 4. Ordered logit models predicting perceived impact of tracking app use.

	Perceived impact					
	Model 3A[a] (n = 411)			Model 3B[b] (n = 411)		
	β	SE	p	β	SE	p
Covariates						
Age	< .01	.01	.608	.01	.01	.270
Gender [c]	.44	.23	.053	.55	.20	.038*
Season: Spring[d]	.23	.33	.489	.07	.34	.842
Season: Summer[d]	.14	.24	.557	.08	.24	.754
Data transmission	.08	.11	.042	-	-	-
Tracking app use						
Baseline tracking app use	.39	.08	<.001**	.29	.08	<.01**
Intended tracking app use	.06	.02	.012*	.04	.02	.088
Logged app use	.24	.14	.093	-	-	-
Self-reported app use	-	-	-	.80	.17	<.01**
Physical activity						
Baseline Physical Activity	−.01	.02	.811	−.05	.02	.054
Intended Physical Activity	.02	.01	.037*	.01	.01	.213
Logged Movement	< .01	< .01	.953	-	-	-
Self-Reported Physical Activity	-	-	-	.04	.01	.001**

Note. [a]Model 3A examines tracking app impact using logged data; [b]Model 3B is estimated using self-reported data; [c]Gender reference group: male; [d]Season reference group: autumn. *$p \leq .05$; **$p < .01$.

effects" in the age of mobile media. In Study 1, we identified overlapping views of tracking apps and physical activity, implying an interplay between people's perceptions of mobile media and their mobile behavior. In Study 2, as predicted by the TAM and TPB, intentions for tracking apps and physical activity were shown to predict self-reported app use and physical activity; however, intentions were not predictive of logged app use or movement (respectively). Moreover, despite participants reporting that the apps "impacted" their activity level, neither self-reported nor logged tracking app use was related to logged movement in daily life.

Although mHealth apps hold promise as a tool for increasing physical activity, findings from Study 2 suggest that tracking app use may have limited influence on real-world behavior. Self-reported tracking app use was not associated with self-reported physical activity, and logged app use was not associated with logged movement. These results add to the body of evidence showing a limited role of mHealth apps in increasing physical activity (e.g., Lynch et al., 2020). Importantly, our study was designed to capture naturalistic use of tracking apps, prioritizing ecological validity over direct interventions and causal inference. In turn, future research should examine this relationship for heavier users of tracking apps and those engaging with specific goals to increase their daily movement. The lack of a relationship in our real-world dataset may reflect that tracking apps require less deliberation than physical activity; going on a run requires setting aside time, getting dressed, finding a route, etc. By contrast, tracking apps can be set to automatically run in the background, raising the question of whether more usage is required for apps to be effective. Indeed, some work suggests that people do use tracking apps more for self-monitoring than for exercise or fitness (Payne et al., 2015), undermining the notion that mHealth apps are meant to enact direct behavior change.

Taken together, our two studies illustrate the complex relationships between mobile media and everyday movement, along with the need for research to further investigate their links (Ross et al., 2022). It may be that the proposed, or presumed, effects of tracking apps on physical activity are more indirect. Results from Study 1 suggest that people's perceptions of tracking apps are related to how they think about physical activity in general—and these shared perceptions were seen for attitudes, behavioral control, and norms. Therefore, our perceptions of tracking technology may be as important as the technology itself in influencing decisions to engage in physical activity. From this angle, mHealth apps have the potential to help people by working in the background to influence the perceptions that underlie behavioral intentions.

Outside the null relationship found between tracking app *usage* and real-world movement, our studies further our understanding of behavioral intentions, along with their links to real-world behavior. Our findings affirm the robust intention–behavior connection in the context of physical activity (McEachan et al., 2011), and now in the domain of tracking app use. Here, physical activity and self-reported intentions consistently predicted self-reported physical activity and tracking app use, respectively (controlling for past behavior). Yet intentions were not associated with our logged measures. This intention–behavior divergence may reflect the tendency to answer questions about their behavior in a consistent manner, as suggested by the overlapping views of tracking apps and physical activity. Alternatively, this divergence supports previous findings showing TPB variables are more effective at predicting self-reported behaviors than objective measures (McEachan et al., 2011). Notably, our data adds to the body of work revealing inconsistencies between perceived (self-reported) and recorded (logged) behaviors. We found that the self-reported physical activity and logged movement estimates were only moderately correlated (r = .27), which may reflect the fact that our logged measure does not account for some forms of physical activity. By contrast, in the case of tracking apps, we found that self-reported and logged estimates and were strongly correlated (r = .71), suggesting that participants had a relatively accurate view of their tracking app use.

Another key takeaway from our findings was the emergence of a perception gap—that is, participants perceived that tracking apps were having a bigger "impact" on their behavior than they actually did. Other studies have illustrated that people's ideas about how much physical activity they are getting may not reflect actual amounts (Crum & Langer, 2007). Here, those who self-reported and logged greater use of tracking apps also perceived that tracking apps exerted a stronger impact on their physical activity. These findings make sense when considering the findings from Study 1, where those with more positive attitudes towards tracking apps also had more positive attitudes toward physical activity. Consequently, it may be fruitful to consider the ways that mHealth apps influence how people *think* about their health progress. Individuals who have been successful at achieving a health goal, for example, may find visualized markers and progress badges as self-affirming. In other words, tracking apps may bolster the extent to which individuals believe in their own ability to enact behavior change, indirectly contributing to physical activity via a self-fulfilling prophecy. Future work can investigate these perceptual processes more directly, including users' own folk theories tied to mHealth apps (Kanthawala et al., 2019), using both quantitative and qualitative approaches.

Over time, tracking apps may reward people who already engage in healthy behavior, rather than create new healthy habits. This explanation is supported by the strong predictive role of past behavior in the Study 2 models. Without the underlying motivation to build long-term habits, the reinforcing and reaffirming potential of mHealth apps is likely to unravel—or even backfire by displaying the lack of progress. If physical-activity tracking app use represents an outcome (rather than a cause) of individuals' health tendencies, then future research necessitates a new perspective on mHealth perceptions. Studies must continue to explore the fusion of theoretical perspectives from health communication and media psychology, as theorizing has largely remained separate. In doing so, researchers should evaluate the differential roles of *attitudes* (i.e., general beliefs regarding the benefits/costs of apps) and *perceived impact* (i.e., self-perceived influence of apps on their own and others' specific behavior) of mHealth apps. In addition, future work can explore how perceptions of mobile health and physical health behaviors are related to perceived mobile affordances (Schrock, 2015) or the psychological connection between users and their smartphones (Ross & Bayer, 2021). By expanding theorizing in this way, we can begin to integrate key variables and processes associated with mobile media use not accounted for in models like the TAM and TPB.

In sum, regardless of whether mHealth apps can solve the "physical inactivity epidemic" (Fenton, 2005), we argue that the *perception* that mHealth matters is significant. In some cases, this perception may represent a misattribution of mobile media effects, as some individuals may overly attribute health progress to a given technology. The self-perceived impact of mobile media, and potential exaggeration of their effects, warrants comparison to core communication theories tied to the "presumed influence" of mass media (Gunther & Storey, 2003). In contrast to such mass media theories (e.g., third person effect), we highlight how individuals may (mis)attribute the effects of personal health technologies. Future work can pursue the precise mechanisms of such mobile media effects just as past work has done with mass media effects (see McLeod et al., 2017, for a review). In doing so, it may become clearer how distinct self-processes interact with tracking technologies at large, as well as which media effects heuristics become salient in different domains. As health technologies become increasingly ingrained in our daily living, and particularly our mobility (Pawlak, 2020; Singleton, 2019), untangling these psychological mechanisms is vital.

From a methodological standpoint, we showcase the potential of measuring movement for mobile communication and media psychology studies (Bayer et al., 2023; Ross et al., 2022), with special relevance in contested areas of research such as mHealth. In doing so, our investigation illustrates the importance of measuring both self-reported and logged outcomes to gain a fuller picture of daily technology and health behaviors. Without collecting such measures in parallel, researchers are likely to overlook established and emergent perception–behavior gaps that are central to the study of media effects. Nonetheless, there are several limitations to note. First, our study leveraged participants' personal phones, which may be preferable to asking participants to carry an additional device that is less embedded in their personal routine (Kuntsche & Labhart, 2013), but may exclude those who use independent tracking devices (i.e., without smartphone-linked apps). Second, similar to many mobile sensing studies, our study also relies on a non-representative sample of Android users. Although Android users have been found to be demographically similar to users of other phone types (Shaw et al., 2016), more representative, probability-based samples are needed to provide generalizability.

In addition, it is possible that the weak link between tracking app usage and physical activity in our data is due to the challenge of isolating effective apps or app behaviors. Given the wide range of smartphone usage and potential tracking apps, our sensing-based measures may overlook beneficial uses within apps or subsets of apps. It is also possible that certain subgroups, such as individuals hoping to lose weight (Qin et al., 2021), would benefit more than the student and community sample recruited in our investigation, or the positive potential of mHealth app use may depend on the varied motives that drive users (Klenk et al., 2017). Notably, our self-reported data implied that different participants understand tracking apps in diverse ways. For example, several participants reported using Pokémon GO to track their steps, while other users of the app did not view Pokémon catching as physical activity tracking. Measurement challenges also may have played a role in our estimation of physical activity: Our logged measure of physical activity captured only activity involving direct movement (e.g., running, walking, biking), sidestepping other activity behaviors (e.g., running on a treadmill, swimming, weightlifting) or activities that occurred when participants did not carry their phones. Likewise, while we recorded apps that were linked to wearables, our data collection overlooks direct engagement with wearables (e.g., Apple Watch, Fitbit). Such devices allow users to continuously track their physical activities and may reflect a different pattern of behavior than mHealth app usage on a phone. Follow-up work should thus assess other forms of physical activity while simultaneously attending to direct engagement with wearables.

Conclusion

Although tracking apps are widely used, questions about their effects on physical activity remain. We sought to fuse the TAM and TPB frameworks to better understand the shared relationships between mHealth technology and physical activity perceptions (Study 1), along with their links to real-world behavior (Study 2). We found that individuals' views of tracking apps reflected their broader views toward physical activity. In addition, we found that more frequent use of tracking apps was associated with seeing them as being more impactful on their health behavior, suggesting a potential indirect (or presumed) influence of mHealth apps for some users. Conversely, no direct relationships were detected between tracking app use and daily movement. We hope our results can be used to guide the design of future mHealth campaigns and apps—in parallel—given the increasingly interwoven nature of mobile behaviors.

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Notes

1. See https://osf.io/bfnpz/ for OSM, datasets, and analysis scripts.
2. See https://osf.io/d56cx/ for an overview of the overall project design and measurement.
3. Alternative models performed during our robustness check revealed a significant effect for H2a. See OSM and RMarkdown for full results.
4. Alternative models performed during our robustness check revealed an insignificant effect for H3a. See OSM and RMarkdown for full results.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*, 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2002). *Constructing a TPB questionnaire: Conceptual and methodological considerations*. http://people.umass.edu/aizen/pdf/tpb.measurement.pdf

Ajzen, I. (2003). *Theory of planned behaviour questionnaire*. https://doi.org/10.13072/midss.649.

Armitage, C. J. (2005). Can the theory of planned behavior predict the maintenance of physical activity? *Health Psychology*, *24*(3), 235–245. https://doi.org/10.1037/0278-6133.24.3.235

Barkley, J. E., Lepp, A., Santo, A., Glickman, E., & Dowdell, B. (2020). The relationship between fitness app use and physical activity behavior is mediated by exercise identity. *Computers in Human Behavior*, *108*, 1–6. https://doi.org/10.1016/j.chb.2020.106313

Bayer, J. B., Reinecke, L., & Vanden Abeele, M. (2023). Psychological perspectives on mobile media: A flyover review. *Mobile Media & Communication*, *11*(110), 107–117. https://doi.org/10.1177/20501579221134369

Beauducel, A., & Herzberg, P. Y. (2006). On the performance of maximum likelihood versus means and variance adjusted weighted least squares estimation in CFA. *Structural Equation Modeling-a Multidisciplinary Journal*, *13*(2), 186–203. https://doi.org/10.1207/s15328007sem1302_2

Beldad, A. D., & Hegner, S. M. (2018). Expanding the technology acceptance model with the inclusion of trust, social influence, and health valuation to determine the predictors of German users' willingness to continue using a fitness app: A structural equation modeling approach. *International Journal of Human-Computer Interaction*, *34*(9), 882–893. https://doi.org/10.1080/10447318.2017.1403220

Boase, J., & Ling, R. (2013). Measuring mobile phone use: Self-report versus log data. *Journal of Computer-Mediated Communication*, *18*(4), 508–519. https://doi.org/10.1111/jcc4.12021

Byambasuren, O., Sanders, S., Beller, E., & Glasziou, P. (2018). Prescribable mHealth apps identified from an overview of systematic reviews. *npj Digital Medicine*, *1*, 1–12. https://doi.org/10.1038/s41746-018-0021-9

Centers for Disease Control and Prevention. (2020a). *How much physical activity do adults need?* https://www.cdc.gov/physicalactivity/basics/adults/index.htm.

Centers for Disease Control and Prevention. (2020b). *Lack of physical activity*. https://www.cdc.gov/chronicdisease/resources/publications/factsheets/physical-activity.htm

Chaiken, S., Pomerantz, E. M., & Giner-Sorolla, R. (2014). Structural consistency and attitude strength. In Petty, R. E., & Krosnick, J. A. (Eds.), *Attitude strength: Antecedents and consequences*. Psychology Press.

Cho, H. (2011). Theoretical intersections among social influences, beliefs, and intentions in the context of 3g mobile services in Singapore: Decomposing perceived critical mass and subjective norms. *Journal of Communication*, *61*(2), 283–306. https://doi.org/10.1111/j.1460-2466.2010.01532.x

Cho, S. J., & Tian, Y. (2021). Investigating the role of communication between descriptive norms and exercise intentions and behaviors: Findings among fitness tracker users. *Journal of American College Health*, *69*(4), 452–458. https://doi.org/10.1080/07448481.2019.1679819

Cialdini, R. B., Reno, R. R., & Kallgren, C. A. (1990). A focus theory of normative conduct—recycling the concept of norms to reduce littering in public places. *Journal of Personality and Social Psychology*, *58*(6), 1015–1026. https://doi.org/10.1037/0022-3514.58.6.1015

Courneya, K. S. (1995). Understanding readiness for regular physical-activity in older individuals: An application of the theory of planned behavior. *Health Psychology*, *14*(1), 80–87. https://doi.org/10.1037/0278-6133.14.1.80

Crum, A. J., & Langer, E. J. (2007). Mind-set matters: Exercise and the placebo effect. *Psychological Science*, *18*(2), 165–171. https://doi.org/10.1111/j.1467-9280.2007.01867.x

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Dzewaltowski, D. A., Noble, J. M., & Shaw, J. M. (1990). Physical-activity participation—social cognitive theory versus the theories of reasoned action and planned behavior. *Journal of Sport & Exercise Psychology*, *12*(4), 388–405. https://doi.org/10.1123/jsep.12.4.388

Fenton, M. (2005). Battling America's epidemic of physical inactivity: Building more walkable, livable communities. *Journal of Nutrition Education and Behavior*, *37*, S115–S120. https://doi.org/10.1016/s1499-4046(06)60211-x

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Addison-Wesley.

Fishbein, M., & Ajzen, I. (2010). *Predicting and changing behavior: The reasoned action approach*. Psychology Press.

Gunther, A. C., & Storey, J. D. (2003). The influence of presumed influence. *Journal of Communication*, *53*(2), 199–215. https://doi.org/10.1111/j.1460-2466.2003.tb02586.x

Hall, A. K., Cole-Lewis, H., & Bernhardt, J. M. (2015). Mobile text messaging for health: A systematic review of reviews. *Annual Review of Public Health*, *36*, 393–415. https://doi.org/10.1146/annurev-publhealth-031914-122855

Hamilton, K., & White, K. M. (2008). Extending the theory of planned behavior: The role of self and social influences in predicting adolescent regular moderate-to-vigorous physical activity. *Journal of Sport and Exercise Psychology*, *30*(1), 56–74. https://doi.org/10.1123/jsep.30.1.56

Herrmann, L. K., & Kim, J. (2017). The fitness of apps: A theory-based examination of mobile fitness app usage over 5 months. *Mhealth*, *3*, 2. https://doi.org/10.21037/mhealth.2017.01.03

Hoj, T. H., Covey, E. L., Jones, A. C., Haines, A. C., Hall, P. C., Crookston, B. T., & West, J. H. (2017). How do apps work? An analysis of physical activity app users' perceptions of behavior change mechanisms. *JMIR mHealth and UHealth*, *5*(8), e114. https://doi.org/10.2196/mhealth.7206

Kanthawala, S., Joo, E., Kononova, A., Peng, W., & Cotten, S. (2019). Folk theorizing the quality and credibility of health apps. *Mobile Media & Communication*, *7*(2), 175–194. https://doi.org/10.1177/2050157918796859

Ketikidis, P., Dimitrovski, T., Lazuras, L., & Bath, P. A. (2012). Acceptance of health information technology in health professionals: An application of the revised technology acceptance model. *Health Informatics Journal*, *18*(2), 124–134. https://doi.org/10.1177/1460458211435425

Klenk, S., Reifegerste, D., & Renatus, R. (2017). Gender differences in gratifications from fitness app use and implications for health interventions. *Mobile Media & Communication*, *5*(2), 178–193. https://doi.org/10.1177/205015791769155

Krebs, P., & Duncan, D. T. (2015). Health app use among US mobile phone owners: A national survey. *Journal of Medical Internet Research*, *3*(4), e4924. https://doi.org/10.2196/mhealth.4924

Kuntsche, E., & Labhart, F. (2013). Using personal cell phones for ecological momentary assessment: An overview of current developments. *European Psychologist*, *18*(1), 3–11. https://doi.org/10.1027/1016-9040/a000127

Li, C. H. (2016). Confirmatory factor analysis with ordinal data: Comparing robust maximum likelihood and diagonally weighted least squares. *Behavior Research Methods*, *48*(3), 936–949. https://doi.org/10.3758/s13428-015-0619-7

Lobelo, F., Kelli, H. M., Tejedor, S. C., Pratt, M., McConnell, M. V., Martin, S. S., & Welk, G. J. (2016). The wild wild west: A framework to integrate mHealth software applications and wearables to support physical activity assessment, counseling and interventions for cardiovascular disease risk reduction. *Progress in Cardiovascular Diseases*, *58*(6), 584–594. https://doi.org/10.1016/j.pcad.2016.02.007

Lomborg, S., Thylstrup, N. B., & Schwartz, J. (2018). The temporal flows of self-tracking: Checking in, moving on, staying hooked. *New Media & Society*, *20*(12), 4590–4607. https://doi.org/10.1177/1461444818778542

Lynch, C., Bird, S., Lythgo, N., & Selva-Raj, I. (2020). Changing the physical activity behavior of adults with fitness trackers: A systematic review and meta-analysis. *American Journal of Health Promotion*, *34*(4), 418–430. https://doi.org/10.1177/0890117119895204

McCallum, C., Rooksby, J., & Gray, C. M. (2018). Evaluating the impact of physical activity apps and wearables: Interdisciplinary review. *JMIR mHealth and UHealth*, *6*(3), e58. https://doi.org/10.2196/mhealth.9054

McEachan, R. R. C., Conner, M., Taylor, N. J., & Lawton, R. J. (2011). Prospective prediction of health-related behaviours with the theory of planned behaviour: A meta-analysis. *Health Psychology Review*, *5*(2), 97–144. https://doi.org/10.1080/17437199.2010.521684

McKay, F. H., Cheng, C., Wright, A., Shill, J., Stephens, H., & Uccellini, M. (2018). Evaluating mobile phone applications for health behaviour change: A systematic review. *Journal of Telemedicine and Telecare*, *24*(1), 22–30. https://doi.org/10.1177/1357633X16673538

McLeod, D. M., Wise, D., & Perryman, M. (2017). Thinking about the media: A review of theory and research on media perceptions, media effects perceptions, and their consequences. *Review of Communication Research*, *5*, 35–83. https://doi.org/10.12840/issn.2255-4165.2017.05.01.013

Michie, S., Yardley, L., West, R., Patrick, K., & Greaves, F. (2017). Developing and evaluating digital interventions to promote behavior change in health and health care: Recommendations resulting from an international workshop. *Journal of Medical Internet Research*, *19*(6), e232–e232. https://doi.org/10.2196/jmir.7126

National Center for Health Statistics. (2018). *Health, United States, 2018*.

Pawlak, J. (2020). Travel-based multitasking: Review of the role of digital activities and connectivity. *Transport Reviews*, *40*(4), 429–456. https://doi.org/10.1080/01441647.2020.1728418

Payne, H. E., Lister, C., West, J. H., & Bernhardt, J. M. (2015). Behavioral functionality of mobile apps in health interventions: A systematic review of the literature. *JMIR mHealth and UHealth*, *3*(1), e20. https://doi.org/10.2196/mhealth.3335

Qin, Y., Wang, X., & Namkoong, K. (2021). A meta-analysis of the overall effect of mHealth physical activity interventions for weight loss and the moderating effect of behavioral change theories, techniques, and mobile technologies. *Mobile Media & Communication*, *10*(2), 337–359. https://doi.org/10.1177/20501579211054929

Rhodes, R. E., & Dickau, L. (2012). Experimental evidence for the intention-behavior relationship in the physical activity domain: A meta-analysis. *Health Psychology*, *31*(6), 724–727. https://doi.org/10.1037/a0027290

Ross, M. Q., & Bayer, J. B. (2021). Explicating self-phones: Dimensions and correlates of smartphone self-extension. *Mobile Media & Communication*, *9*, 488–512. https://doi.org/10.1177/2050157920980508

Ross, M. Q., Müller, S., & Bayer, J. B. (2022). The psychology of mobile technology and daily mobility. In Matz, S. (Ed.), *The psychology of technology: Social science research in the age of big data* (pp. 125–154). American Psychological Association.

Rosseel, Y., Jorgensen, T. D., Rockwood, N., Oberski, D., Byrnes, J., Vanbrabant, L., Savalei, V., Merkle, E., Hallquist, M., Rhemtulla, M., Katsikatsou, M., Barendse, M., & Scharf, F. (2020, July 31). *Package "lavaan": Latent variable analysis*. http://lavaan.org

Scholer, A. A., Ozaki, Y., & Higgins, E. T. (2014). Inflating and deflating the self: Sustaining motivational concerns through self-evaluation. *Journal of Experimental Social Psychology*, *51*, 60–73. https://doi.org/10.1016/j.jesp.2013.11.008

Schrock, A. R. (2015). Communicative affordances of mobile media: Portability, availability, locatability, and multimediality. *International Journal of Communication*, *9*, 1229–1246.

Shaw, H., Ellis, D. A., Kendrick, L. R., Ziegler, F., & Wiseman, R. (2016). Predicting smartphone operating system from personality and individual differences. *Cyberpsychology Behavior and Social Networking*, *19*(12), 727–732. https://doi.org/10.1089/cyber.2016.0324

Singleton, P. A. (2019). Multimodal travel-based multitasking during the commute: Who does what? *International Journal of Sustainable Transportation*, *14*(2), 150–162. https://doi.org/10.1080/15568318.2018.1536237

Sumaedi, S., & Sumardjo. (2020). Factors influencing internet usage for health purposes. *International Journal of Health Governance*, *25*, 205–221. https://doi.org/10.1108/Ijhg-01-2020-0002

Vanden Abeele, M., Beullens, K., & Roe, K. (2013). Measuring mobile phone use: Gender, age and real usage level in relation to the accuracy and validity of self-reported mobile phone use. *Mobile Media & Communication*, *1*(2), 213–236. https://doi.org/10.1177/2050157913477095

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

von Pape, T. (2020). Autonomous vehicles in the mobility system. In Ling, R., Fortunati, L., Goggin, G., Lim, S., & Li, Y. (Eds.), *The Oxford handbook of mobile communication and society* (pp. 500–514). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190864385.013.33.

Wang, Q., Egelandsdal, B., Amdam, G. V., Almli, V. L., & Oostindjer, M. (2016). Diet and physical activity apps: Perceived effectiveness by app users. *JMIR mHealth and UHealth*, *4*(2), 202–215. https://doi.org/10.2196/mhealth.5114

Yuan, S., Ma, W., Kanthawala, S., & Peng, W. (2015). Keep using my health apps: Discover users' perception of health and fitness apps with the UTAUT2 model. *Telemedicine and e-Health*, *21*(9), 735–741. https://doi.org/10.1089/tmj.2014.0148

Zhao, Y. (2015). *The performance of model fit measures by robust weighted least squares estimators in confirmatory factor analysis*. Department of Educational Psychology, Pennsylvania State University.

Zheng, E. L. (2021). Interpreting fitness: self-tracking with fitness apps through a postphenomenology lens. *AI & Society*. https://doi.org/10.1007/s00146-021-01146-8

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