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Tracking Myself: Assessing the Contribution of Mobile Technologies for Self-Trackers of Weight, Diet, or Exercise

EULÀLIA PUIG ABRIL

Department of Communication, University of Illinois at Chicago, Chicago, Illinois, USA

For individuals trying to lose or maintain weight, self-tracking their weight, diet, or exercise is important. In the past, different tracking modes have been examined, like paper and pencil, memory, or personal digital assistants. But the recent advancement and adoption of mobile technologies could also result in easier and simpler self-tracking. However, little is known about self-trackers, their tracking modes, and the absolute or relative contribution of each tracking mode at the population level. This study fills this gap by (a) comparing self-trackers' characteristics across tracking modes and against nontrackers and (b) testing the relationship between mobile self-tracking and tracking outcomes using a representative sample of data from the Pew Internet and American Life Project from 2012. Controls in the model include demographics, technology use, and health indicators. Results suggest that mobile self-trackers are younger and more educated and that mobile self-tracking is a positive contributor and the best tracking mode.

Over the past three decades, new technologies such as computers and medical devices have helped individuals self-track weight, diet, or exercise (WDE) more efficiently, but it is the development and adoption of mobile technologies that has transformed the way people self-track health indicators (Klasnja & Pratt, 2012). *Self-tracking* is defined as the deliberate, regular collection of measurable data about the self, like weight, food intake, or visits to the gym (Swan, 2009, p. 509). Currently, nearly 70% of adults in the United States track a health indicator, and 87% of these self-track WDE (Fox & Duggan, 2013).

More than one third of adults in the United States are obese, and two thirds are overweight (Ogden, Carroll, Kit, & Flegal, 2013).[1] The routine of tracking WDE patterns can be valuable for behavioral weight loss or maintenance programs. For instance, the U.S. Department of Health and Human Services recommends tracking individuals' physical activities to help control weight loss and maintenance (Office of Disease Prevention and Health Promotion, 2016). Ultimately, being obese and being overweight are associated with a myriad of adverse health risks (Ogden et al., 2013, p. 809). Thus, studies seeking to curtail the incidence of obesity—like this one—are pressing.

According to self-regulation theory (Bandura, 1991), self-tracking supports improvements in goal maintenance such as eating healthy or becoming physically active. By self-tracking, individuals are able to identify patterns that need to be modified or reinforced (Seals, 2007) and act on them. Thus, frequent WDE self-tracking leads to weight loss or maintenance (Grave, Calugi, & El Ghoch, 2013; Spring, Duncan, & Janke, 2013), which in turn is associated with better health (Centers for Disease Control and Prevention, 2013).

The goals of this study are to assess (a) the characteristics of Americans currently self-tracking WDE, (b) the most utilized tracking mode and the characteristics of individuals using each tracking mode, and (c) the unique contribution of mobile devices to self-reported behaviors related to WDE. Data from the Pew Internet and American Life Project are used, and analyses control for a host of demographics, technology use, and health indicators. I draw on self-regulation theory (Bandura, 1991) to situate self-tracking within health behavior change (Burke, Wang, & Sevick, 2011). Mobile technologies are broadly understood, including cell phones, smartphones, and tablets. So far, this study is the first to compare mobile self-tracking to several other tracking modes using a representative sample of the U.S. adult population.

Study results shed light on the relationship between tracking modes in the U.S. population and population characteristics as well as help clarify which tracking modes may be critical to reducing obesity and achieving better health. Findings may also help readers understand the contribution of mobile technologies in self-regulation. Practical results from the analyses may be useful to public health personnel and policy practitioners working on behavioral intervention programs related to WDE.

Literature Review

Self-Regulation, Self-Tracking, and Health

Most people believe that being successful at staying on a diet or avoiding junk food is a matter of willpower (the ability to resist impulses). However, motivational and self-regulatory skills are what matters. Self-regulation is central to human causal processes. Self-regulation entails the formation of beliefs about

Address correspondence to Eulàlia Puig Abril, Department of Communication, University of Illinois at Chicago, 1007 West Harrison Street, 1152B BSB, MC 132, Chicago, IL 60607, USA. E-mail: eulalia@uic.edu

[1]Overweight is defined as a body mass index greater than or equal to 25; for obese, it is greater than or equal to 30 (World Health Organization, 2016).

what is doable and the anticipation of potential consequences, so it is the mediation of the effects of most external influences (e.g., junk food availability) on individuals, providing the basis for purposeful action (Bandura, 1991). Through this process of forethought, individuals become motivated (Bandura, 1991). One important avenue to achieving self-regulatory success is consistent self-tracking (Bandura, 1991; Burke, Wang, et al., 2011).

Using self-tracking in this process leads to heightened awareness of behaviors. Scholars have identified greater recognition or simply awareness of behaviors and the circumstances surrounding those behaviors as a mechanism contributing to weight loss and/or maintenance (Burke, Wang, et al., 2011; Carels et al., 2005). With awareness or greater recognition, individuals may implement strategies to counteract problems with diet or routine adherence (Carels et al., 2005; Wing & Hill, 2001). For instance, not noticing weight loss within a week may trigger more visits to the gym or eliminating sugary desserts for a while—both healthier options.

Researchers agree that self-tracking or self-monitoring weight, diet, and/or exercise contributed to weight loss and maintenance (Butryn, Phelan, Hill, & Wing, 2007; Grave et al., 2013; Linde, Jeffery, French, Pronk, & Boyle, 2005; O'Neil & Brown, 2005; Spring et al., 2013; Wing & Hill, 2001). These findings have been validated in randomized controlled trials (Burke, Wang, et al., 2011; Butryn et al., 2007; Spring et al., 2013; Wing & Phelan, 2005) and for individuals of different sizes (Baker & Kirschenbaum, 1998; King, Taylor, Haskell, & Debusk, 1988).

Self-Tracking, Tracking Modes, and Individual Characteristics

Although a few studies have uncovered the relationship between self-tracking and WDE, little is known about the attributes of self-trackers. Self-trackers are individuals self-monitoring one or more health indicators (Fox & Duggan, 2013). Data collection can be done via any tracking mode, including paper and pencil or memory, and data need not be pooled or scrutinized. The prevalence of self-trackers in the U.S. adult population is about two thirds, a remarkable number (Fox & Duggan, 2013). But beyond this information, research on self-tracking has relied on studies using homogeneous samples consisting largely of Caucasian and/or female participants (Burke, Wang, et al., 2011; Butryn et al., 2007).

Compounding the modest knowledge about self-trackers is the confusion between self-trackers and self-quantifiers (McFedries, 2013). Self-quantifiers[2] systematically collect quantifiable WDE data *and* data related to body input and output (e.g., heart rate, sleep, calories burned) using wearable technologies. More important, self-quantifiers analyze these data to determine optimal performance levels of their body systems using computational analysis (Smarr, 2012; Swan, 2009). However, these self-quantifying behaviors are not typically observed in about two thirds of the population. Self-quantifiers tend to be middle-aged, Caucasian, educated, and affluent urban dwellers (Briggs, 2014; Lee, 2014)—that is, not the majority.

Therefore, I make a distinction between self-trackers and self-quantifiers. Let self-quantifiers be a subset of self-trackers with the distinctive characteristic that self-quantifiers track with (or at least in part with) wearable devices containing sensors *and* analyze the data beyond self-awareness. So, self-tracking is a broader activity. Given that there is no previous study whose data and analysis resulted in generalizable findings of the self-tracker population, the following research question is proposed:

> Research Question 1: What are the characteristics of WDE self-trackers?

A follow-up question involves self-trackers' tracking mode and use of technology, which also could help distinguish self-trackers from self-quantifiers. Studies have relied on different tracking modes to monitor self-tracking: memory (Butryn et al., 2007; Gokee-Larose, Gorin, & Wing, 2009); paper and pencil (Burke, Conroy, et al., 2011; Hurling et al., 2007), or more specifically paper diaries (Carels et al., 2005; Tsai et al., 2007; Turner-McGrievy et al., 2013); Internet or software programs (Gokee-Larose et al., 2009; Turner-McGrievy et al., 2013); medical devices (Mattila et al., 2008); personal digital assistants (Burke, Conroy, et al., 2011); mobile devices (Haapala, Barengo, Biggs, Surakka, & Manninen, 2009; Hurling et al., 2007; Mattila et al., 2008; Tsai et al., 2007; Turner-McGrievy et al., 2013); and/or wearable devices (Consolvo et al., 2008). However, none of these studies used a representative sample. Hence, the distribution of technology among the U.S. population and the characteristics of individuals using said technologies remain unknown, prompting two research questions:

> Research Question 2: What are WDE self-trackers' most used tracking modes?

> Research Question 3: Do the characteristics of individuals using each tracking mode differ?

Mobile Self-Tracking

Notwithstanding the importance of regular self-tracking, it is a labor-intensive activity, and consistency (adherence) is often difficult (Tsai et al., 2007). Tracking mode is a factor related to consistency. For instance, results comparing technologies showed that self-tracking with a personal digital assistant led to improved adherence and greater weight loss than paper and pencil (Burke, Conroy, et al., 2011). Similarly, using software to store self-tracking data (e.g., a scale with a digital memory) led to more adherence in weight self-tracking than using memory (Gokee-Larose et al., 2009). Thus, technology seems to improve self-tracking frequency in weight loss treatments (Burke, Conroy, et al., 2011; Khaylis, Yiaslas, Bergstrom, & Gore-Felton, 2010).

The most significant technological advance likely to affect self-tracking is mobile technologies. The universal use of mobile phones, currently at more than 90% adoption (Zickuhr, 2013), offers many advantages for tracking health behaviors. Computational and advanced capabilities (Anderson & Raine,

[2]There has been a lot of buzz about the quantified-self movement (Feiler, 2014), which maintains a website, holds local meetings and a yearly conference (see http://quantifiedself.com), and counts on a group of steadfast devotees (Smarr, 2012).

2014), context awareness features such as sensing (Klasnja & Pratt, 2012), plus individuals' attachment to their phones (Klasnja & Pratt, 2012; Ventä, Isomursu, Ahtinen, & Ramiah, 2008) now allow mobile technologies to self-track in a way that computers or medical devices could not because computers are harder and more inconvenient to move and medical devices do not typically have powerful technical capabilities. In addition, mobile phones can capture information in real time that can be contextually and ecologically focused, creating rich data based on an individual's natural environment and experiences (Gasser et al., 2006; Klasnja & Pratt, 2012; Patrick, Griswold, Raab, & Intille, 2008). Finally, mobile technologies can generate frequent instant reports of behaviors and measures, thereby decreasing recall bias in self-reporting as well as participant burden (Tsai et al., 2007).

Although data are limited (for a review, see Buhi et al., 2013), various uses of mobile devices to self-track have shown positive results. For instance, an app prototype from a generation before smartphones was found to lead to more regular self-tracking than a paper diary (Tsai et al., 2007). Similarly, mobile apps were found to be better than personal digital assistants and paper and pencil, leading to more frequent self-monitoring and higher intention to exercise (Hurling et al., 2007; Turner-McGrievy et al., 2013). Findings regarding tracking mode do not seem to be conclusive (Turner-McGrievy et al., 2013), except for the case of mobile tracking (see Buhi et al., 2013).

However, the conclusion on mobile advantage was tested only in randomized controlled trials by assigning participants to a tracking mode. But what happens when participants select their own tracking mode or adopt it organically? Does the mobile advantage hold? Furthermore, much of the research comparing different tracking modes had other components in the study that were easily confounded with tracking mode, such as external rewards (Gokee-Larose et al., 2009) or social support (Hurling et al., 2007), making it difficult to know whether the effect was due to mobile tracking mode per se or due to other factors. Taking into account the advantage of mobile devices for self-tracking shown in experimental research and the importance of WDE tracking frequency in mediating weight loss or maintenance, the following hypothesis is proposed:

Hypothesis 1: Using a mobile device to self-track WDE will be positively related to frequency of tracking.

Aside from effects on consistency, self-tracking is also related to better health (Centers for Disease Control and Prevention, 2013; Hull et al. 2016; Pingree et al., 2010), lower health risks (Williams et al., 2002), and a lower risk of mortality (Idler & Benyamini, 1997). Likewise, improved weight and/or exercise practices as a consequence of self-tracking (Butryn et al., 2007; Grave et al., 2013; Haapala et al., 2009) lead to better health (Centers for Disease Control and Prevention, 2013; Imayama et al., 2011).

The capabilities unique to mobile devices, such as location and contextual information (e.g., calendar or data mined from social networking sites), can be used to alert individuals to opportunities for healthy activities and local resources relevant to their health (e.g., nearby restaurants that serve healthy food or the suggestion to take a walk after a long meeting). Such diverse prompts could provide a dynamic way to keep individuals engaged with their health goals over extended periods of time, thus building on the benefits of self-tracking (Klasnja & Pratt, 2012). A final hypothesis is proposed:

Hypothesis 2: Using a mobile device to self-track WDE will be positively related to overall health status.

Mobile phone tracking may be more efficacious than other tracking modes in achieving WDE goals because of the mode's unique capabilities (phone, texting, sensing, audio and video, storage, mobility, processing speed, and ubiquity, among the most important) compared to a computer, medical device, paper and pencil, or memory. However, to date no study has tested the relative contribution of tracking modes to tracking frequency or overall health status. Most research has only looked at one or two tracking modes at a time, with a few looking at three (e.g., Turner-McGrievy et al., 2013). Therefore, the following research question is posed:

Research Question 4: Does tracking with a mobile device lead to better WDE-related outcomes compared to other tracking modes?

Method

Data

This study relied on U.S. representative data from the Pew Internet and American Life Project's Health Tracking Survey collected between August 7 and September 6, 2012 ($N = 3{,}014$). Telephone interviews were conducted by landline and cell phone in either English or Spanish among the U.S. adult population. The response rate was 11.5% for landlines and 6.6% for cell phones (using the American Association for Public Opinion Research standards).[3] The sample was weighted to account for the disproportionately stratified sample (oversampling of African American and Hispanic respondents), the overlapping landline and cell sample frames, and differential nonresponse associated with sample demographics. The weighting was accomplished in multiple stages to balance national parameters for age, gender, education, and ethnicity. Weights ensured census representation. The margin of error for the weighted data was ±2.4 percentage points.

The data set was chosen for the present study because it is a probability sample of the U.S. adult population and because of the detail in the measurement of health tracking data. The survey quantified both self-tracking and tracking for others (acting as caregivers). However, the survey did not ask whether the tracking-related indicators applied to self or others. Therefore, only those who self-tracked WDE exclusively for themselves were kept for analysis, generating a sample size of 530.

[3]Even though these are low response rates, they are within the acceptable norm (Pew Research Center, 2016).

Measures

Outcome Variables

Frequency of tracking was measured merging two items that were asked under skip logic. The first item requested how often participants updated their records in general, with the possible answers being "never," "only when something comes up," or "on a regular basis." For those updating their records on a regular basis, a follow-up question then requested the specific frequency on a scale from *less than once a month* to *several times a day*. The merged variable thus measured frequency on a scale from 0 = *never* to 7 = *several times a day* (M = 2.28, SD = 1.98). The variable frequency of tracking is consistent with studies assessing the frequency of behaviors such as weighing (Butryn et al., 2007; Linde et al., 2005).[4] The literature provides examples of self-reports of tracking behavior correlating imperfectly with actual tracking behavior (Prince et al., 2008). However, others studies have shown that this relationship holds (see Aadahl & Jørgensen, 2003; Butryn et al., 2007).[5]

Overall health status was obtained by asking participants to self-rate their own health on a scale from 1 = *poor* to 4 = *excellent* (M = 3.25, SD = 0.69). This is the same question asked in most national and international surveys inquiring about overall health status, including the RAND Corporation (www.rand.org), Gallup (www.gallup.com), or the World Health Organization (www.who.org). With minor variations, this robust single-item measure has been used extensively worldwide for more than half a century (Bowling, 2005). Hence, it represents a valid and acceptable measure of overall health status.

Independent Variables

The following dichotomous variables were indicators of whether participants tracked their weight using a mobile device (9% did), a computer or Internet program (4% did), a medical device (1% did), paper and pencil (19% did), or memory (62% did). I adopted McClendon's (1994) approach to converting a multinomial variable into dichotomous variables in which all categories but one (in this case mobile tracking, the variable of interest) are present in the analysis.

Control Variables

Several demographic variables were gathered, including gender (54% female); age (M = 43.10; SD = 18.54); education (Mdn = some college); income (Mdn = $40;000–$50;000); whether participants were caring for children younger than 18 years (26% were); whether participants lived with a partner (53% did); whether participants lived in rural areas (8% did); and measures for ethnicity and race—African American (11%), Hispanic (3%), Asian (4%), and Native American (1%).

In order to monitor the ability and usage of technology when testing tracking mode, I used the following variables as controls: Internet use, with an additive measure of two dichotomous items, use of the Internet at least occasionally and use of e-mail (sending or receiving) at least occasionally (M = 1.59, SD = 0.76; r = .79); for mobile phone use, responses from two dichotomous filter questions (having a cell phone [Filter 1], having a smartphone [Filter 2]) and access to the Internet via mobile device were collapsed into the following categories: 0 = *no mobile phone,* 1 = *cell phone but not smartphone,* 2 = *smartphone but no mobile Internet,* 3 = *uses Internet via smartphone* (M = 1.49, SD = 1.06). Thus, mobile phone use was measured with three items, creating a continuum of respondents' progressive level of involvement in using a cell phone.

In terms of health indicators, the following variables were used. First, I considered whether participants had health insurance (84% did), including work-related, Medicare, Medicaid, privately purchased, or military/veteran's coverage.[6] Second, I measured whether participants had had an emergency episode in the past 12 months with an additive two-item measure tapping whether individuals had faced a serious medical emergency or crisis and whether they had gone to the emergency room or been hospitalized unexpectedly in the past year (M = .20, SD = .51; r = .46). Finally, I considered whether individuals had any chronic condition (30% did), including diabetes, high blood pressure, asthma, bronchitis, emphysema, lung condition, heart disease, heart failure, heart attack, cancer, or any other chronic health problem.

Analysis

To assess population differences, I used t tests and nonparametric (Mann–Whitney U) tests (Research Question 1, Research Question 3). Similarly, nonparametric (Mann–Whitney U) tests were used to test for differences in tracking mode among WDE self-trackers (Research Question 2).

To test the hypotheses and Research Question 4, I conducted regression analyses. Independent variables were organized in the following blocks: demographics, technology use, health indicators, and tracking mode—the variable set of interest.

Results

Characteristics of Self-Trackers and Comparison of Self-Trackers Across Tracking Modes

WDE self-trackers were more likely to be female, were more educated, had more income, had fewer children, lived less in rural areas, were less likely to be Hispanic, used the Internet more, used mobile technologies more, were more insured, had more recent emergencies, and had fewer chronic conditions than non-self-trackers (see Table 1 for details). With

[4]The most used measures for frequency of tracking in the literature are the number of diaries completed (for paper-and-pencil tracking modes), the frequency of log-ins, or the frequency of self-reported weight (Burke, Wang, et al., 2011).

[5]What might be at stake here is the complexity of the behavior. For complex or tedious behaviors (e.g., specific caloric intake or concrete physical activity), devices that track those behaviors are far more reliable than self-reports (Lichtman et al., 1992). However, for less demanding behaviors (e.g., self-reports with a broader framework for the frequency, like daily, twice a day, or every week), the correlation between self-reports and actual behavior is significantly higher (Boase & Ling, 2013).

[6]This survey was administered before the Affordable Care Act, also known as Obamacare, had launched. Therefore, this item followed the format of previous surveys and did not inquire about additional purchase options for health coverage.

Table 1. Mean/percentage comparison between WDE self-trackers and nontrackers

Characteristic	WDE self-trackers	Nontrackers	Effect size (r)
Demographics			
Age	43.10	43.76	.00
Gender (female)	54%**	46%**	.08
Education	4.58***	3.94***	.16
Income	4.98***	4.13***	.16
Children	26%***	37%***	.13
Partner	53%	55%	.02
Rural	8%***	15%***	.11
African American	11%	12%	.01
Hispanic	3%***	12%***	.17
Asian	4%*	2%*	.05
Native American	1%	1%	.03
Technology use			
Internet use	1.59***	1.43***	.09
Mobile phone use	1.49***	1.17***	.15
Health indicators			
Insurance (yes)	84%***	71%***	.16
Recent emergency	0.20*	0.14*	.07
Chronic condition (yes)	30%*	35%*	.05
N	530	638	

Note. N = 1,168. Cell entries are means or percentages (for dichotomous variables). Two-tailed tests are t tests for continuous variables and nonparametric (Mann–Whitney U) tests for dichotomous variables. In terms of effect size, $r \leq .1$ is small, $r > .1 \leq .5$ is medium, and $r > .5$ is large (Rosnow & Rosenthal, 1996). WDE = weight, diet, or exercise.
*$p \leq .05$. **$p \leq .01$. ***$p \leq .001$.

Table 2. Tracking mode comparison among WDE self-trackers (in order of magnitude)

Tracking mode	WDE self-trackers
Memory	65%***
Paper	20%***
Mobile device	9%***
PC/Internet	4%***
Medical device	1%

Note. N = 530. Two-tailed tests are nonparametric (Mann–Whitney U) tests. The comparison is with respect to the category below. WDE = weight, diet, or exercise; PC = personal computer.
***$p \leq .001$.

respect to age, living with a partner, being African American, being Asian, and being Native American, there were no differences between the two groups (see Table 1). Most indicators pointed to WDE self-trackers as being of a higher socioeconomic status than their non-self-tracking counterparts, but in terms of health, results did not seem conclusive. On the one hand WDE self-trackers were more insured and had fewer chronic conditions, but on the other hand WDE self-trackers had more recent emergencies than those not self-tracking (Research Question 1).

Table 3. Comparison of individual characteristics among WDE self-trackers (by tracking mode)

Characteristic	Mobile	PC/ Internet	Medical	Paper	Memory
Demographics					
Age	31.06	38.86	71.32*	46.70*	42.72*
Gender (female)	59%	56%	51%	60%	51%
Education	5.33	5.64	2.00*	4.39*	4.56
Income	5.96	6.00	3.64	4.69	4.94
Children	34%	43%	0%	27%	25%
Partner	55%	57%	79%	48%	55%
Rural	4%	6%	0%	10%	8%
African American	10%	6%	0%	17%	9%
Hispanic	0%	4%	39%*	5%	2%
Asian	10%	5%	0%	0%	5%
Native American	1%	0%	0%	0%	1%
Technology use					
Internet use	1.96	1.98	0.39*	1.55*	1.61*
Mobile phone use	2.22	1.98	0.61*	1.40*	1.47*
Health indicators					
Insurance (yes)	82%	100%	59%	81%	85%
Recent emergency	.23	.08	.67	.30	.18
Chronic condition (yes)	17%	13%	88%*	34%*	29%
N	48	23	6	108	345

Note. N = 530. Cell entries are means or percentages (for dichotomous variables). Entries with 0% are approximations. Tests are two-tailed: t tests for continuous variables and nonparametric tests (Mann–Whitney U tests) for dichotomous variables. Comparisons are set up using mobile tracking as the reference category and using the Holm method (Seaman, Levin, & Serlin, 1991; Zweifel, 2014) to control Type I error, which also works for nonnormal variables (Zweifel, 2014). Each row entails testing four Holm comparisons (for a total of 64 Holm comparisons). For medical self-tracking, tests have very little power because of a low n. WDE = weight, diet, or exercise; PC = personal computer.
*Significance for each comparison less than $p \leq .05$ (family-wise).

Among WDE self-trackers, results indicated a significant preference for memory over paper and pencil, paper and pencil over mobile devices, mobile devices over Internet/personal computer (PC), and Internet/PC over medical device (see Table 2 for details). Thus, the most used modes were memory, paper and pencil, and mobile devices, respectively (Research Question 2).

Comparing the characteristics of WDE self-trackers across tracking modes, there are findings to report (see Table 3 for details). Mobile self-trackers were younger than those tracking with a medical device, memory, or paper and pencil; were more educated than those tracking with a medical device or memory; were less likely to be Hispanic than those tracking with a Medical device; used the Internet and mobile technologies more than those tracking with a medical device, memory, or paper and pencil; and had fewer chronic conditions than those tracking with a medical device. However, there were no differences across tracking modes for the following variables: gender,

Table 4. Regression analysis

Characteristic	Tracking frequency	Overall health status
Demographics		
Age	−.23***	−.09
Gender (female)	−.06	−.09*
Education	.10	.08
Income	−.17***	.21***
Children	−.03	−.16**
Partner	.29***	−.01
Rural	−.07	.09*
African American	−.07	−.01
Hispanic	−.07	−.06
Asian	.01	.05
Native American	.04	.09*
Incremental R^2	7.1%***	21.2%***
Technology use		
Internet use	−.07	.00
Mobile phone use	−.07	.06
Incremental R^2	0.4%	0%
Health indicators		
Insurance	.07	−.14**
Recent emergency	.02	−.12**
Chronic condition	−.05	−.28***
Incremental R^2	0%	8.9%***
Tracking mode		
PC/Internet	−.09*	−.01
Medical device	−.09*	−.03
Paper	−.31***	−.14**
Memory	−.50***	−.11*
Incremental R^2	10.4%***	0.5%
Total R^2	17.9%***	30.6%***

Note. $N = 530$. All cell entries are standardized ordinary least squares regression coefficients (betas). R^2 is the adjusted value. PC = personal computer
*$p \le .05$. **$p \le .01$. ***$p \le .001$, two-tailed tests.

income, having children younger than 18, living with a partner, living in rural areas, being African American, being Asian, being Native American, having insurance, and having had a recent emergency (Research Question 3).

The Contribution of Mobile Technologies

Results from the regression analysis (see Table 4) showed that even though some control variables were significant (e.g., age, gender, income), they were not systematically of the same sign across outcomes. However, the case was different for self-tracking WDE with a mobile device. Results indicated that using a mobile device to self-track WDE over PC/Internet, a medical device, paper and pencil, and memory was positively related to frequency of tracking. Thus, support for Hypothesis 1 was substantiated. The contribution of tracking mode accounted for more than half of the variance explained, which was 17.9% in this model.

Findings also indicated that the use of a mobile device to self-track WDE over paper and pencil and memory, but not over PC/Internet or a medical device, was positively related to overall health status. Hence, support for Hypothesis 2 was only partially substantiated. The tracking mode set contributed 0.5% to the incremental variance, which totaled 30.6% in this model.

In conclusion, mobile devices are better than all other tracking modes considered here in improving frequency of tracking but superior only to paper and pencil and memory when it comes to overall health status (Research Question 4).

Discussion

Given the widespread obesity in the United States (Centers for Disease Control and Prevention, 2013), experts need to explore venues for remediating it that are effective, affordable, and easy to implement. Self-tracking WDE is a promising, theory-based (Glanz, Lewis, & Rimer, 1990) avenue to reduce obesity, operating via—and enhancing—self-regulation (Bandura, 1991). Without self-regulation—the ability to operate in one's environment—obesity reduction is difficult (Bandura, 1988), and relapse is high (Wing, Tate, Gorin, Raynor, & Fava, 2006).

Americans have self-tracked WDE using a variety of new technologies (e.g., medical devices, personal digital assistants), but mobile devices offer the potential to self-track faster and more reliably vis-à-vis other tracking modes. To explore mobile self-tracking, this study applied U.S. representative data from Pew to assess self-tracker characteristics, examine most used tracking modes, compare self-trackers across tracking modes, and assess the relationship between mobile tracking and tracking frequency and overall health status. The question was whether mobile adoption carried additional gains compared to other tracking modes.

Results showed that those who self-tracked WDE were females with a higher socioeconomic status who used the Internet and mobile technologies more than those not self-tracking. Despite self-trackers being confused with self-quantifiers (McFedries, 2013), the self-tracker profile did not match the self-quantifier profile (Briggs, 2014; Lee, 2014). On the one hand, self-trackers were more affluent and educated—like self-quantifiers. But on the other hand, self-trackers were *not* more Caucasian, middle-aged, or likely to be urban dwellers than their non-self-tracker counterparts. Hence, aligning self-trackers with self-quantifiers may not be warranted. The results here point to the proposition that self-quantifiers may be a subgroup of self-trackers, although this was not formally tested.

The preferred tracking mode among the U.S. adult population was memory, followed by paper and pencil. Mobile devices were only a distant third. Again, this result bolsters the premise that self-quantifiers may not be equal to self-trackers. Using mobile and wearable technology is crucial to being called a self-quantifier (Lee, 2014). Among self-trackers, mobile trackers were significantly different in several ways from trackers using a medical device, memory, and paper and pencil but not different from trackers using the Internet or a PC. The first contribution of this study is thus a depiction of self-trackers: A broad group of individuals monitoring WDE indicators and using a variety of tools that are not necessarily highly technological.

The study's second contribution is the result that using a mobile device to self-track is related to a higher frequency of tracking and better overall health status even though mobile self-tracking was only at 9% usage. Results also signal that mobile tracking's contribution to frequency of tracking was significantly larger than that of any other tracking mode. The contribution to overall health status was not larger than that of all other tracking modes, possibly because of the low impact of tracking mode on overall health status. Overall, these findings resonate with the existing liter ature—on the so-called mHealth—that situates mobile use at the forefront of factors influencing desirable health outcomes (Kailas, Chong, & Watanabe, 2010; Lane, Heddle, Arnold, & Walker, 2006). Memory and paper may be the most utilized tracking modes, but they do not represent the best way to track.

From a public health perspective, the impact of mobile WDE self-tracking on frequency of tracking constitutes a critical avenue for research. The exceptionally higher frequency of self-tracking achieved with mobile devices makes them second to no other method. Moreover, given the value of self-tracking to self-regulation—facilitating a process of self-consciousness—it makes behavior maintenance more likely (Swan, 2009). The positive relationship between mobile tracking and overall health status, which no other tracking mode accomplished, is bolstered by the evidence linking overall health status—self-rated health—to a lower risk of mortality (Idler & Benyamini, 1997). Thus, mobile tracking is linked to one of the most important indicators of public health, namely, mortality.

A third contribution of this study is that it was based on a probability sample—a request voiced by researchers (Burke, Wang, et al., 2011)—which is more generalizable than nonprobability samples or laboratory studies. Although recent studies have attempted to connect mobile tracking to better outcomes in terms of weight loss or maintenance, most studies were conducted with homogenous groups and with results not applicable to the general population (Gasser et al., 2006; Gerber, Stolley, Thompson, Sharp, & Fitzgibbon, 2009; Haapala et al., 2009). For instance, Kumanyika and colleagues (2000) suggested that selection criteria to participate in randomized controlled trials were typically biased (e.g., not applicable to the general population) to achieve experimental control (Gerber et al., 2009). In addition, self-selection may be problematic because participants are often highly motivated (Gasser et al., 2006). Finally, Kumanyika and his collaborators pointed to the nutritional and behavioral counseling that typically accompanied these trials, which do not necessarily represent a real-life setting (Gerber et al., 2009), and to the bias in reporting results, which excluded data from individuals leaving the study (Haapala et al., 2009). The present study, though, utilized representative survey data from self-trackers and controlled for an array of potentially confounding variables.

In the realm of health communication, a fourth contribution takes another form, posing more questions than answers. Although the findings here provide support for mobile technologies as potential routes to weight loss or maintenance, the precise mechanism of the process remains unknown. Researchers argue that mobility and ubiquity, locality or context awareness, and almost universal availability may make it easier to generate rich data tailored to the individual (Gasser et al., 2006; Klasnja & Pratt, 2012; Patrick et al., 2008). However, the particular contributions of these or other affordances will have to be assessed in future research. A strong candidate to explain these mechanisms may be some of the mobile features, such as instant information, reminders or alerts, remote monitoring, decision-making tools, or social support resources (Gustafson et al., 2011).

Although the results here are intriguing, there are some limitations to consider. For instance, the relative importance of WDE in the outcome variables could not be directly assessed from the data. Weight, diet, and exercise self-trackers were not asked to indicate which of the three elements they were monitoring. Although this limitation may represent a hurdle to moving forward with future research, it ultimately points out that mobile self-tracking may affect all three. Furthermore, the outcome measures related to self-reported indicators but not directly to weight loss or maintenance indicators, for which there were no data. Previous research has substantiated the relationship between self-tracking (*and* frequency of tracking) and weight loss or maintenance (Butryn et al., 2007; Grave et al., 2013; Spring et al., 2013; Wing & Hill, 2001), but this was not formally tested here and constitutes a thriving area of research. Finally, although the study implies directional results (from self-tracking to frequency of tracking and improved overall health), the nature of the cross-sectional data used did not allow formal testing of this directional relationship, and so it remains an open question. Still, previous research has shown that this is the proper causal order (Imayama et al., 2011; Khaylis et al., 2010).

Despite these limitations, the findings presented here are very encouraging. Self-tracking has a host of positive health-related outcomes, and with 91% of Americans owning a cell phone (Zickuhr, 2013) the potential is notable. Future research should examine the capacity for persuasion because this study was concerned only with those already self-tracking. Likewise, there may be more individuals self-tracking WDE who *also* engage in tracking for others, or who are self-tracking medical symptoms, which highlights another potential area of mobile tracking research.

As technology evolves, so must approaches to tackling health problems. mHealth has already shown its capabilities to make great strides in the advancement of health care and health communication (Sherry & Ratzan, 2012) and continues to show potential (Klasnja & Pratt, 2012; Patrick et al., 2008). Tracking health information that can be easily captured, stored, and shared on mobile devices may have a substantial impact on improving and maintaining positive health behaviors like reducing obesity. The hope is that the present study will promote a discussion about potential benefits of mobile self-tracking on health outcomes related to weight, diet, and exercise among researchers and practitioners.

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