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An Evaluation of Students' Interest in and Compliance With Self-Tracking Methods: Recommendations for Incentives Based on Three Smartphone Sensing Studies

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Abstract

Self-tracking consists of recording the behaviors that occur in one's daily life. Self-tracking studies can provide researchers with *passively sensed* information about individual's daily behaviors and environments and *actively logged* information (e.g., self-reports). This method has great promise for obtaining detailed records of behavior in naturalistic contexts, but it is not known what factors would motivate individuals to participate in self-tracking studies. Here, we analyze students' interest in self-tracking and their compliance with self-tracking using smartphones. Three dimensions of self-tracking motivations were identified: productivity and health behaviors, well-being and daily activities, and social life on campus; these motivations were related to participation preferences and individual characteristics. We also present evidence from three studies that suggest personalized feedback combined with other incentives (course credit toward a class assignment, monetary compensation, or a prize reward) can be an effective recruitment strategy. Recommendations for the design of future self-tracking studies are presented.

Keywords

research methods, naturalistic observation, smartphone sensing, smartphone applications, ecological momentary assessment, self-tracking, behavioral observation

Self-Tracking Tools for Behavioral Observation in Daily Life

Self-tracking (also known as "life logging") consists of recording the behaviors that occur in one's daily life. It is often undertaken by individuals to gain insight into their own behavioral or psychological patterns (Gurrin, Smeaton, & Doherty, 2014). Common motivations for self-tracking include understanding health-related behavioral patterns; maximizing work performance; and examining interactions among mental, behavioral, and environmental variables (Choe, Lee, Lee, Pratt, & Kientz, 2014). There are many approaches to self-tracking and a number of tools are available to measure psychologically meaningful aspects of one's life (for a list, see http://quantifiedself.com/guide/).

An individual's biometrics (e.g., step count, heart rate), contextual information (e.g., location, noise level, being around other people), and behavioral patterns (e.g., physical activity, social interactions) can all be self-tracked using ambient (*passive sensing*) or user-initiated (*active logging*) data collection methods. As summarized in Table 1, a broad array of self-tracking tools are available, including wearable devices (cameras, audio recorders, biometric sensors), smartphones, laptop and desktop computers, and environmental mobile sensors (e.g., sensors embedded in household items or smart homes). Such tools have been used in past research to examine participants' health behaviors (e.g., Cellini, McDevitt, Mednick, & Buman, 2016; Doherty, Lemieux, & Canally, 2014; Harrison, Marshall, Berthouze, & Bird, 2014), daily activities (e.g., Mehl, Pennebaker, Crow, Dabbs, & Price, 2001; Qiu, Doherty, Gurrin, & Smeaton, 2010; Shaikh, Molla, & Hirose, 2008), and their symptoms of mental (e.g., Saeb et al., 2015; R. Wang et al., 2016) and physical illness (e.g., Ossig et al., 2016; Thilarajah, Clark, & Williams, 2016).

Self-tracking tools are appealing to researchers because they can provide detailed portraits of the behaviors and experiences

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Table 1. Overview of Self-Tracking Tools.

Tools	Description	Variables Captured and Example Tools		Example Studies	Measures Collected		
		Passive Sensing	Active Logging		Biometrics	Contexts	Behaviors
Wearables							
Cameras	Wearable cameras record images or video, usually from the perspective of the wearer	Periodically or semicontinuously takes pictures or videos For example, SenseCam, Narrative Clip	User takes pictures of significant events, food eaten, and so on For example, commercial photo camera	Dickie et al. (2004); Hodges et al. (2006); Silva, Pinho, Macedo, and Moulin (2013); Qiu, Doherty, Gurrin, and Smeaton (2010); and Reddy et al. (2007)	×	✓	✓
Audio recorders	Wearable audio recorders capture features of the ambient environment and user activities (e.g., social interactions, daily activities, and locations)	Periodically samples brief recordings of ambient sounds For example, Electronically Activated Recorder	User records significant events and daily activities For example, commercial voice recorder	Ellis and Lee (2006); Mehl, Pennebaker, Crow, Dabbs, and Price (2001); Shah, Mears, Chakrabarti, and Spanias (2012); Shaikh, Molla, and Hirose (2008)	×	✓	✓
Biometric sensors	Wearable devices interact with individual's movement and personally entered data to track numerical health indexes and monitor progress toward self-set goals (e.g., calories burned, step count, and heart rate)	Continuously monitors physical activity levels via accelerometer sensors For example, Jawbone, Fitbit	Users initiates sleep tracking or heart rate measurements For example, Fitbit, Withings Wifi Bodyscale	Cellini et al. (2016); J. Kim (2014); Middelweerd et al. (2015); Ossig et al. (2016); and Thilarajah, Clark, and Williams (2016)	✓	×	✓
Smartphones	Smartphone apps collect data from surveys, phone logs, and onboard sensors to track many kinds of behaviors (e.g., social interactions, daily activities, mobility patterns, and environmental features)	Periodically or continuously collects from smartphone system log (e.g., calls, texts) and onboard sensors (e.g., microphone, GPS, and accelerometer) For example, Easy M, StudentLife	User responds to experience sampling surveys via text messages or a smartphone app For example, SurveySignal	Alderson-Day and Fernyhough (2015); Doherty, Lemieux, and Canally (2014); Fisher and To (2012); Gotink et al. (2016); Hurlburt and Akhter (2006); Kimhy et al. (2006); Richards et al. (2015); Swendeman et al. (2015); Wang et al. (2014)	✓	✓	✓
Computers	Laptop and desktop computers record user-initiated behavior, (e.g., in an e-diary or through a questionnaire) and can also be used to collect data from web browsing histories, online educational platform use, and social media accounts	Records browsing histories, engagement with learning platforms, usage behavior For example, RescueTime, Quizlet, Khan Academy, and TimeAware	User responds to surveys or electronic diaries via web-based platforms For example, Qualtrics, MyPersonalityProject	Crutzen, Roosjen, and Poelman (2013); Y. H. Kim et al. (2016); Kobayashi and Inamasu (2015); Ruiperez-Valiente, Munoz-Merino, Leony, and Kloos (2015); Wang, Li, Zheng, and Chang (2012)	×	✓	✓
Mobile sensors in environment	Sensors in environment (e.g., in smart homes) can passively track without requiring participant to wear or carry a device	Records from smart home devices, temperature settings, electricity consumption For example, infrared camera and motion sensor	No studies to our knowledge	Demiris and Hensel (2008); Fahad, Khan, and Rajarajan (2015); Jalal, Kim, and Kim (2012)	×	✓	✓

Note. In the rightmost columns, the following symbols are used: ✓ means the tool is typically used to collect the measure; × means the tool is not typically used to collect the measure.

of participants as they go about their lives. However, it is unclear whether people are interested in participating in studies that use self-tracking methods. What might motivate people to track their own behaviors and psychological states? And which self-tracking tools would people be interested in using? There are a number of reasons why people might be hesitant to take part in studies that use self-tracking. For example, self-tracking tools may be perceived as uncomfortable or burdensome to participants and participants may find sensor-based data collection to intrude on their privacy; such factors could result in low compliance with passive sensing. Participants may also find notifications to respond to ecological momentary assessments (EMAs) to be repetitive or disruptive to their daily activities, which could lead to low compliance with active logging. Indeed, past research has found participants become less compliant over time during longitudinal tracking studies (e.g., becoming less responsive to completing surveys, forgetting to carry, wear, or charge devices; Mehl & Hollerhan, 2007; Striegel et al., 2013; R. Wang et al., 2014) and that technical problems can also diminish compliance rates (e.g., bugs in software, data loss, battery depletion, broken devices; Harrison et al., 2014; Striegel et al., 2013). To assist in the design of studies that would benefit from integrating such tools, a better understanding of participants' interest in and compliance with self-tracking is needed.

The Promise of Smartphones as a Self-Tracking Tool

Among the different self-tracking tools, smartphones stand out as being particularly promising for psychological science (Gosling & Mason, 2015; Harari et al., 2016; Miller, 2012). Smartphones can be used both to collect behavioral data passively from embedded mobile sensors (Lane et al., 2010) and to obtain data actively, such as via EMAs that prompt participants to respond to questions in situ as they go about their day (Wrzus & Mehl, 2015). Consequently, smartphones can capture a wide range of behaviors including social interactions (e.g., call and text-message logs), daily activities (e.g., search queries, app usage), and mobility patterns (e.g., locations visited, distance traveled; Harari et al., 2016). As of 2014, approximately 64% of adults in the United States already have smartphones (Pew Research Center, 2014) and the number of smartphone users is increasing in countries around the world (Pew Research Center, 2015), making smartphone-based research designs particularly attractive to researchers interested in real-world behavior.

To evaluate the viability of using these methods for behavioral data collection in psychological studies, this article focuses on participants' interests in self-tracking and their compliance rates when participating in smartphone-based studies. The first set of analyses examines a cohort of participants' potential motivations for self-tracking and the psychological characteristics associated with their motivations. The second set of analyses examines participants' compliance with self-tracking when using smartphones. Across three self-tracking studies that had different incentives for participation, we present trends in behaviorally assessed compliance for both passive sensing (number of days sensing app is recording data) and active logging (number of days EMAs are recorded).

Method

Participants and Procedure

Details about the participants and procedures (study design, incentives, self-tracking tools, measures) for the three samples presented in this article are provided in Table 2. The shared design features across all three samples included the following: (1) participants' use of smartphones as a self-tracking tool, (2) the ability to self-track using passive sensing and active logging, and (3) the incentive of personalized feedback based on participants' self-tracking data. In each sample, sample size was determined by recruiting as many participants as possible within the pool of potential participants. We aimed to maximize power for detecting small to medium effects (e.g., relationships between individual differences and EMAs) by using intensive within-person designs: continuous passive sensing assessments and repeated active logging assessments. Below, we describe the main differences that distinguish the three samples, which included the study durations, recruitment strategies, the use of different smartphone-based tracking systems, and the use of additional incentives.

Sample 1 (S1): Course credit + feedback. S1 consisted of one 5-week wave of data collection, for a total of 35 possible self-tracking days. In S1, participants were recruited from an online introductory psychology course that had 1,537 students enrolled. Participation was voluntary, and the main incentive was personalized feedback. In addition to personal feedback, participants could earn credit toward a relevant class assignment about everyday behavioral patterns if they self-tracked for 5 or more days. Participants could choose to use e-mail (via questions presented using Qualtrics software) or a smartphone sensing application (Easy M; Lathia, 2015) as the self-tracking tool. For the purposes of this article, we focus on a subset of the participants who responded to a survey about their interest in self-tracking ($N = 1,440$; 94% of the total possible participants) and those who used their smartphones for passive sensing ($N = 595$; 39%) and active logging ($N = 563$; 37%).

Sample 2 (S2): Compensation + feedback. S2 consisted of two 2-week phases of data collection that were 3 months apart, for a total of 28 possible self-tracking days. In S2, 118 participants were recruited by advertising the study at a freshman orientation fair, through undergraduate advisers, undergraduate tutors, student unions, and by posting fliers within various departments and on freshman Facebook groups. In addition to personal feedback, participants received £10 for completing the first phase of data collection and up to £25 for the second phase of data collection (if they completed 60% or more of the active logging component). Compensation was higher for the second collection phase to incentivize participation during the final examination period. Due to unexpected technical difficulties with the Android application software, participants with

Table 2. Overview of the Samples and Procedures Across the Three Self-Tracking Studies.

Sample	*N*	Demographics	Design Description	Participation Incentives	Self-Tracking Tools	Summary of Measures
S1: Course credit + feedback	1,440	Age ($M = 18.84$, $SD = 2.03$); 39% male; 40% White Academic class: 60% Freshmen 23% Sophomores 10% Juniors 5% Seniors 2% Did not report	Students within an online introductory psychology course could self-track their psychological experiences and behaviors as a main feature of the course	Course credit toward a relevant class assignment; personalized feedback (during the study)	Smartphone app (Easy M); e-mail-based surveys (Qualtrics)	Individual characteristics; interest in self-tracking; EMAs about activities, personality, and mood states
S2: Compensation + feedback	118	Age ($M = 19.10$, $SD = 1.60$); 37% male; 70% White Academic class: 100% Freshmen	First-year students were recruited for a study on student well-being and adjustment to university life	Monetary compensation; personalized feedback (after the study)	Smartphone app (Easy M, My Student Life); web-based EMA surveys via text messages (SurveySignal)	Individual characteristics; EMAs about activities and mood; daily diaries
S3: Prize reward + feedback	64	Age ($M = 22.20$, $SD = 3.11$); 63% male; 38% White Academic class: 22% Freshmen 17% Sophomores 20% Juniors 17% Seniors 23% Grad Students	Students within a computer science department were recruited for a study about tracking behavioral lifestyles	Prize reward for being in top 50% of data collectors; personalized feedback (during the study)	Smartphone app (CampusLife); wearable device (Microsoft Band)	Individual characteristics; EMAs about stress and mood

Note. See Appendix B of the Supplemental Materials for the list of EMA items used in S1–S3. Individual characteristics refers to series of surveys collected as part of the studies, including demographics, personality, and well-being measures. Links to information about the self-tracking tools used can be found in the References. EMAs = ecological momentary assessments.

Android phones (31%) used two different smartphone sensing applications for passive sensing and active logging during the two phases of the study: Phase 1 (Easy M; Lathia, 2015) and Phase 2 (My Student Life; Mehrotra, 2016). Participants with iPhones (69%) responded to text message prompts via SurveySignal (Hofmann & Patel, 2015) during both phases for active logging alone because the sensing applications used in the study were not designed to run on the iOS platform. No participants were excluded from the sample.

Sample 3 (S3): Prize reward + feedback. S3 consisted of two 9-week waves of data collection that were 1 month apart, for a total of 62 possible self-tracking days. In S3, 64 participants were recruited by advertising the study via e-mail to all students in a computer science department. In addition to personal feedback, participants received a self-tracking tool (a wearable device called Microsoft Band; Microsoft, 2015) as a reward for being in the top 50% of self-trackers in the study. The number of available Microsoft Bands limited the sample size, but nearly all students who expressed interest were recruited. In addition, 9 students from the first wave participated in the second wave of data collection in exchange for an additional monetary compensation. For these participants, we excluded the compliance estimates from the second wave of data collection because they had unique incentives for participating during that time. In terms of excluded participants, five participants were dropped from the study because of consistent noncompliance with self-tracking. Participants with Android and iPhones used the same smartphone sensing application (CampusLife) for both passive sensing and active logging.

Self-Report Assessment of Students' Interest in Self-Tracking

Ninety-four percent ($N = 1{,}440$) of the possible participants from S1 completed a 2-item questionnaire about their motivations to participate in self-tracking studies and their self-tracking preferences (e.g., frequency of EMAs, types of behavioral data collected). Participants first received the following prompt: "Tracking behavior is becoming increasingly easy to do. Smartphone apps and other web-based platforms (like those made available for this assignment) are being used by many people to quantify their everyday behaviors for self-tracking purposes. Psychologists are interested in behavior tracking for designing interventions that aim to promote positive well being among college students. What would motivate you to participate in a self-tracking program?"

Participants then responded to the following questions: (1) I would participate in a self-tracking program if it helped me . . . (the 16 response options ranged from improve academic performance to not applicable, would not participate) and (2) How would you want to track your psychological states and/or behaviors? (the 10 response options ranged from responding to EMAs once or more times a day to not applicable, would not participate). Participants were instructed to select all the response options that applied to them, so they were able to endorse more than one option for each question. Tables 3 and 4 present the complete list of response options for each item and the descriptive statistics for the items (for additional correlations between each of the individual motivations and individual participation preference items, see Supplemental Table S1).

Behavioral Assessment of Students' Compliance in Self-Tracking

In S1–S3, behaviorally assessed compliance measures were computed from the self-tracking data collected. Compliance was assessed in two ways: (1) *passive tracking compliance* was computed by estimating whether each participant had sensor data collected from the smartphone sensing app for each day of the study period and (2) *active logging compliance* was computed by estimating whether each participant had responded to an EMA for each day of the study period. To examine trends in these two compliance measures, the compliance estimates were converted into percentages to reflect the degree of participants' engagement with self-tracking during the study period (i.e., the number of passive/active compliant participants per day divided by the total number of participants in the study sample, multiplied by 100). The two behavioral compliance measures provided complementary information about compliance by providing estimates of the general duration of self-tracking (passive sensing) and degree of engagement with self-tracking (active logging). Table 5 presents the descriptive statistics and correlations between the two compliance measures.

Results

Were Students Interested in Self-Tracking?

Ninety-six percent of the students surveyed in S1 reported that they would participate in a self-tracking program. Compared to the students who expressed interest in self-tracking, students who reported that they would not participate were more likely to be male, older, and less agreeable (Table 3). To examine the motivations and participation preferences of the students who were interested in self-tracking, we first describe the most and least frequently endorsed individual items. We then provide an overview of the principal components analysis (PCA) results and examine the individual characteristics that are associated with interest in self-tracking programs by correlating the motivation dimensions with participation preferences and individual difference measures (for additional correlations between each of the individual motivations and participation preferences with the individual difference measures, see Supplemental Tables S2–S3).

Motivations for self-tracking and participation preferences. As shown in Table 3, the motivations for self-tracking that were most frequently endorsed by the students were to improve academic performance, manage time and to-do lists, track exercise or diet patterns, and understand when they are most productive. The motivations that were least endorsed were to track daily activities in a diary or journal format, to find study groups for classes, to keep track of illness and symptoms, and to regulate

Table 3. Base Rates and Interitem Correlation for Self-Tracking Motivations.

Variables	*N*	%	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Improve academic performance	1,170	81	—	[.30, .39]	[.18, .28]	[.21, .30]	[.18, .28]	[.21, .31]	[.29, .38]	[.12, .22]	[.23, .32]	[.21, .31]	[.20, .29]	[.05, .15]	[.11, .21]	[.14, .24]	[.02, .13]	[−.33, −.24]
2. Manage time, to-do lists	920	64	.34* (.00)	—	[.31, .40]	[.15, .25]	[.20, .30]	[.32, .41]	[.27, .37]	[.22, .31]	[.31, .40]	[.22, .31]	[.21, .31]	[.13, .23]	[.22, .31]	[.23, .32]	[.16, .26]	[−.22, −.12]
3. Understand when productive	889	62	.23* (.00)	.36* (.00)	—	[.14, .24]	[.15, .24]	[.22, .31]	[.20, .30]	[.22, .31]	[.21, .30]	[.15, .25]	[.20, .30]	[.20, .30]	[.27, .37]	[.19, .29]	[.16, .26]	[−.21, −.11]
4. Make friends with other students	552	38	.25* (.00)	.20* (.00)	.19* (.00)	—	[.40, .48]	[.18, .28]	[.26, .35]	[.13, .23]	[.13, .23]	[.14, .24]	[.20, .29]	[.09, .19]	[.12, .22]	[.10, .20]	[.14, .24]	[−.13, −.02]
5. Find study groups for classes	380	26	.23* (.00)	.25* (.00)	.20* (.00)	.44* (.00)	—	[.15, .25]	[.19, .28]	[.21, .31]	[.17, .27]	[.15, .25]	[.15, .25]	[.09, .19]	[.11, .21]	[.22, .32]	[.14, .24]	[−.08, .03]
6. Balance work and social life	771	54	.26* (.00)	.36* (.00)	.27* (.00)	.23* (.00)	.20* (.00)	—	[.27, .36]	[.25, .34]	[.21, .31]	[.23, .33]	[.20, .30]	[.19, .28]	[.25, .35]	[.26, .35]	[.17, .27]	[−.17, −.07]
7. Improve physical health	799	55	.34* (.00)	.32* (.00)	.25* (.00)	.30* (.00)	.24* (.00)	.32* (.00)	—	[.31, .40]	[.25, .34]	[.35, .44]	[.30, .39]	[.12, .22]	[.20, .30]	[.22, .32]	[.13, .23]	[−.19, −.09]
8. Track illness or symptoms	384	27	.17* (.00)	.27* (.00)	.26* (.00)	.18* (.00)	.26* (.00)	.29* (.00)	.35* (.00)	—	[.25, .35]	[.21, .31]	[.26, .36]	[.27, .36]	[.26, .35]	[.23, .32]	[.30, .39]	[−.07, .03]
9. Regulate sleep habits	788	55	.28* (.00)	.35* (.00)	.26* (.00)	.18* (.00)	.22* (.00)	.26* (.00)	.29* (.00)	.30* (.00)	—	[.29, .38]	[.22, .32]	[.16, .26]	[.22, .32]	[.19, .29]	[.12, .22]	[−.17, −.07]
10. Track exercise or diet	864	60	.26* (.00)	.27* (.00)	.20* (.00)	.19* (.00)	.20* (.00)	.28* (.00)	.39* (.00)	.26* (.00)	.34* (.00)	—	[.15, .25]	[.16, .26]	[.17, .26]	[.22, .31]	[.15, .25]	[−.20, −.10]
11. Improve mental health	847	59	.25* (.00)	.26* (.00)	.25* (.00)	.24* (.00)	.20* (.00)	.25* (.00)	.35* (.00)	.31* (.00)	.27* (.00)	.20* (.00)	—	[.27, .36]	[.25, .34]	[.16, .26]	[.19, .28]	[−.20, −.10]
12. Track mood	621	43	.10* (.00)	.18* (.00)	.25* (.00)	.14* (.00)	.14* (.00)	.23* (.00)	.17* (.00)	.32* (.00)	.21* (.00)	.21* (.00)	.32* (.00)	—	[.36, .44]	[.23, .32]	[.31, .40]	[−.14, −.04]
13. Track of stress sources	850	59	.16* (.00)	.26* (.00)	.32* (.00)	.17* (.00)	.16* (.00)	.30* (.00)	.25* (.00)	.30* (.00)	.27* (.00)	.22* (.00)	.30* (.00)	.40* (.00)	—	[.26, .35]	[.23, .33]	[−.21, −.11]
14. Regulate social media use	453	31	.20* (.00)	.28* (.00)	.24* (.00)	.15* (.00)	.27* (.00)	.31* (.00)	.27* (.00)	.27* (.00)	.24* (.00)	.27* (.00)	.21* (.00)	.27* (.00)	.30* (.00)	—	[.26, .36]	[−.08, .02]
15. Diary-style activity tracking	354	25	.08* (.00)	.21* (.00)	.21* (.00)	.19* (.00)	.19* (.00)	.22* (.00)	.18* (.00)	.35* (.00)	.17* (.00)	.20* (.00)	.24* (.00)	.35* (.00)	.28* (.00)	.31* (.00)	—	[−.07, .03]
16. N/A, not interested	62	4	−.28* (.00)	−.18* (.00)	−.16* (.00)	−.08* (.00)	−.03 (.32)	−.12* (.00)	−.14* (.00)	−.02 (.46)	−.12* (.00)	−.15* (.00)	−.15* (.00)	−.09* (.00)	−.16* (.00)	−.03 (.21)	−.02 (.50)	—

Note. N refers to number of students who endorsed the item. % refers to the percentage of the sample endorsing the item ($N = 1{,}440$). *p* Values are adjusted for multiple tests. Correlation coefficients with exact *p* values in parentheses are presented below the diagonal and confidence intervals above the diagonal.
$^*p < .01$.

Table 4. Base Rates and Interitem Correlation for Participation Preferences.

Variables	*N*	%	1	2	3	4	5	6	7	8	9	10
Respond to EMAs once a . . .												
1. Day or more times a day	783	54	—	[−.52, −.45]	[−.10, .01]	[−.07, .04]	[.00, .11]	[−.01, .10]	[−.03, .08]	[−.03, .08]	[−.01, .10]	[−.23, −.13]
2. Week or every few weeks	605	42	−.49* (.00)	—	[.18, .28]	[.16, .26]	[−.03, .07]	[.02, .12]	[−.09, .01]	[−.05, .05]	[−.06, .04]	[−.16, −.05]
3. Month or every few months	147	10	−.05 (.08)	.23* (.00)	—	[.54, .61]	[.02, .13]	[.03, .13]	[−.04, .06]	[−.02, .08]	[−.01, .10]	[−.07, .03]
4. Semester or year	112	8	−.02 (.57)	.21* (.00)	.58* (.00)	—	[.03, .13]	[−.01, .10]	[−.03, .08]	[−.02, .08]	[−.02, .08]	[−.03, .07]
Collect data from . . .												
5. Smartphone and sensors	656	46	.05 (.04)	.02 (.49)	.07* (.01)	.08* (.00)	—	[.26, .36]	[.27, .36]	[.26, .35]	[.27, .37]	[−.18, −.08]
6. Online educational platforms	676	47	.05 (.08)	.07* (.01)	.08* (.00)	.04 (.10)	.31* (.00)	—	[.33, .42]	[.28, .37]	[.13, .23]	[−.18, −.08]
7. Web browsing history	485	34	.02 (.35)	−.04 (.12)	.01 (.65)	.02 (.37)	.31* (.00)	.37* (.00)	—	[.46, .54]	[.15, .25]	[−.13, −.03]
8. Social media accounts	614	43	.03 (.33)	.00 (.91)	.03 (.27)	.03 (.21)	.31* (.00)	.32* (.00)	.50* (.00)	—	[.17, .27]	[−.16, −.06]
9. Wearable devices	688	48	.04 (.09)	−.01 (.74)	.04 (.09)	.03 (.28)	.32* (.00)	.18* (.00)	.20* (.00)	.22* (.00)	—	[−.19, −.08]
10. NA, would not participate	56	4	−.18* (.00)	−.11* (.00)	−.02 (.44)	.02 (.40)	−.13* (.00)	−.13* (.00)	−.08* (.00)	−.11* (.00)	−.13* (.00)	—

Note. N refers to number of students who endorsed the item (sample $N = 1{,}440$). % refers to the percentage of the sample endorsing the item. Correlation coefficients with exact *p* values in parentheses are provided below the diagonal and confidence intervals above the diagonal. EMAs = ecological momentary assessments; NA = not applicable.
$^*p < .01$.

Table 5. Descriptive Statistics and Correlations Between Behavioral Compliance Measures.

Studies	*N*	*M*	*SD*	Min	Max	Correlations Within Samples *r*	*p*	95% CI
S1: Course credit + feedback								
Passive sensing	595	13.29	8.44	1	36	.64*	.00	[.58, .69]
Active logging	563	11.81	5.79	1	36			
S2: Compensation + feedback								
Passive sensing	36	16.61	9.08	1	28	.50*	.00	[.21, .71]
Active logging	118	21.47	8.77	1	28			
S3: Prize reward + feedback								
Passive sensing	64	51.25	14.37	12	62	.83*	.00	[.73, .89]
Active logging	63	44.24	16.06	3	62			

Note. N refers to number of participants in each sample who participated in passive sensing or active logging, respectively. *M*—*Max* estimates refer to the number of days participants were compliant with passive sensing or active logging, respectively. CI = confidence interval; *SD* = standard deviation.
$^*p < .01$.

social media use. As shown in Table 4, the participation preferences that were most frequently endorsed by the students were to respond to EMAs one or more times a day, collect data from wearable devices, collect data from online educational platforms, and collect data from smartphone sensors. The participation preferences that were least frequently endorsed were to respond to EMAs once a semester or year and respond to EMAs once a month or every few months.

To determine whether the individual motivation and preference items could be captured by a smaller number of broader dimensions, the 15 motivation items and the 9 preference items (the not applicable items were excluded from the analysis) were subjected to separate PCAs with oblique (promax) rotations. Our large sample size met recommended guidelines for producing stable components (Guadagnoli & Velicer, 1988). Both PCAs extracted three factors with initial eigenvalues exceeding 1, which were retained on the basis of the scree tests and the interpretability of the solutions (Zwick & Velicer, 1986). The PCA solution for the motivation items indicated three components, which accounted for 46% of the variance and were intercorrelated above .30 (*r*s range from .31 to .59). The three components underlying the motivations to self-track were named as follows: (1) productivity and health behaviors, (2) well-being and daily activities, and (3) social life on campus (see Table 6 for factor names and loadings). The PCA solution for the self-tracking preference items indicated three components, which accounted for 59% of the variance and were intercorrelated below .30 (*r*s range from −.16 to .11). The three components underlying the self-tracking preferences were named as follows: (1) passive behavioral tracking, (2) periodic active logging, and (3) daily active logging (see Table 7 for factor loadings).

Productivity and health behaviors. The first component reflected a broad dimension consisting of items emphasizing motivations to improve academic performance, manage time and to-do lists, regulate sleep habits, improve physical health, track exercise or diet habits, balance work and social life, and understand times when they are most productive; these items tapped into a motivation to improve productivity and physical health, so the component was labeled "Productivity and Health Behaviors." Students who were motivated to self-track to improve productivity and a healthy lifestyle were more likely to prefer passive behavioral data collection and responding to EMAs periodically (Table 8). These students were also more likely to be younger in age, of lower academic classes (e.g., freshmen, sophomores), higher in extroversion, and higher in agreeableness, compared to students who were not motivated to monitor their productivity and health behaviors (Table 9).

Well-being and daily activities. The second component reflected a broad dimension consisting of items emphasizing motivations to track mood, record daily activities in a diary-style format, track stress and its sources, track illness or symptoms, and regulate social media use; these items tapped into a motivation to track mental states and daily activities, so the component was labeled "Well-Being and Daily Activities." Students who were motivated to self-track to monitor their well-being were more likely to prefer passive behavioral data collection and responding to EMAs in general (i.e., periodically or daily; Table 8). These students were also more likely to be women, higher in neuroticism, higher in openness, and higher in depression, compared to students who were not motivated to monitor their well-being and daily activities (Table 9).

Social life on campus. The third component reflected a broad dimension consisting of items emphasizing motivations to make friends with other students and find study groups for classes; these items tapped into a motivation to socialize and study with other students, so the component was labeled "Social Life on Campus." Students who were motivated to self-track to increase their social life on campus were more likely to prefer passive behavioral data collection and responding to EMAs periodically (Table 8). These students were also more likely to be younger and of lower academic classes, compared to students who were not motivated to increase their social life on campus (Table 9).

Table 6. Factor Loadings From Principal Components Analysis of Motivations for Self-Tracking.

Variables	PC1: Productivity and Health Behaviors	PC2: Well-Being and Daily Activities	PC3: Social Life on Campus
1. Improve academic performance	**.81**	−.38	.13
2. Manage time, to-do lists	**.73**	−.03	−.05
9. Regulate sleep habits	**.67**	.01	−.1
7. Improve physical health	**.63**	−.05	.15
10. Track exercise or diet	**.62**	.00	−.04
6. Balance work and social life	**.51**	.17	−.02
3. Understand when productive	**.42**	.26	−.09
12. Track mood	−.17	**.86**	−.08
15. Diary-style activity tracking	−.29	**.80**	.17
13. Track of stress sources	.13	**.64**	−.15
8. Track illness or symptoms	.13	**.52**	.09
14. Regulate social media use	.16	**.44**	.08
11. Improve mental health	.24	.34	.11
4. Make friends with other students	.05	−.03	**.82**
5. Find study groups for classes	.02	.05	**.80**

Note. Factor loadings greater than |.40| are presented in boldface type. PC = Principal Component.

Table 7. Factor Loadings From Principal Components Analysis of Self-Tracking Preferences.

Variables	PC1: Passive Behavioral Tracking	PC2: Periodic Active Logging	PC3: Daily Active Logging
7. Collect data from web browsing history	**.76**	−.08	−.01
8. Collect data from social media accounts	**.74**	−.06	−.03
6. Collect data from online educational platforms	**.66**	.03	−.05
5. Collect data from smartphone and sensors	**.65**	.09	.05
9. Collect data from wearable devices	**.51**	.04	.07
4. EMAs once a semester or year	−.04	**.89**	.03
3. EMAs once a month or every few months	−.02	**.88**	−.02
1. EMAs one or more times a day	.00	.15	**.90**
2. EMAs once a week or every few weeks	.03	.18	**−.82**

Note. Factor loadings greater than |.40| are presented in boldface type. EMAs = ecological momentary assessments; PC = Principal Component.

Table 8. Correlations Among the Motivations for Self-Tracking and Participation Preferences.

	Self-Tracking Preferences											
	Passive Behavioral Tracking			Periodic Active Logging			Daily Active Logging			NA, Would Not Participate		
Motivations for self-tracking	*r*	*p*	95% CI	*r*	*p*	95% CI	*r*	*p*	95% CI	*r*	*p*	95% CI
Productivity and health behaviors	.32*	.00	[.27, .36]	.12*	.00	[.06, .17]	.05	.04	[.00, .11]	−.26*	.00	[−.31, −.21]
Well-being and daily activities	.30*	.00	[.25, .34]	.10*	.00	[.05, .15]	.12*	.00	[.07, .18]	−.13*	.00	[−.18, .08]
Social life on campus	.15*	.00	[.10, .20]	.08*	.00	[.02, .13]	−.01	.62	[−.06, .04]	−.07*	.00	[−.13, −.02]
NA, not interested	−.15*	.00	[−.20, −.10]	−.05	.06	[−.10, .00]	.00	.96	[−.05, .05]	.65*	.00	[.62, .68]

Note. Sample 1; $N = 1{,}440$. *p* Values are adjusted for multiple tests. EMAs = ecological momentary assessments; CI = confidence interval; NA = not applicable.
$^{*}p < .01$.

How Well Did Students Comply With Using Smartphones for Self-Tracking?

Overall, participants in S2 and S3 had higher compliance rates than those in S1 (Figure 1). Specifically, an average of 58% of participants in S2 and 83% of participants in S3 complied with passive sensing per day, while only 38% of participants complied in S1. Similarly, an average of 77% of participants in S2 and 70% of participants in S3 complied with active logging per day, while only 34% of participants in S1 complied. In addition, passive sensing compliance rates were generally higher than active logging compliance in S1 and S3, but not in S2. We suspect that the low compliance rates for passive

Table 9. Correlations Between Individual Differences and Motivations for Self-Tracking.

	Motivations for Self-Tracking											
	Productivity and Health Behaviors			Well-Being and Daily Activities			Social Life on Campus			NA, Not Interested		
Individual Differences	r	p	95% CI	r	p	95% CI	r	p	95% CI	r	p	95% CI
Demographics												
Female[a]	.06	.02	[.01, .11]	.09*	.00	[.04, .14]	−.05	.08	[−.10, .01]	−.09*	.00	[−.15, −.04]
Age	−.09*	.00	[−.14, −.04]	−.02	.50	[−.07, .03]	−.08*	.00	[−.13, −.03]	.09*	.00	[.03, .14]
Academic class	−.08*	.00	[−.13, −.03]	.00	.90	[−.05, .06]	−.12*	.00	[−.17, −.07]	.06	.03	[.01, .11]
Personality												
Extroversion	.08*	.01	[.02, .13]	.05	.10	[−.01, .1]	−.04	.17	[−.09, .02]	.01	.74	[−.05, .06]
Agreeableness	.09*	.00	[.04, .15]	.06	.05	[.00, .11]	.00	.92	[−.05, .06]	−.10*	.00	[−.15, −.04]
Conscientiousness	−.02	.54	[−.07, .04]	−.06	.03	[−.12, −.01]	−.05	.06	[−.11, .00]	−.05	.10	[−.10, .01]
Neuroticism	.06	.04	[.00, .11]	.16*	.00	[.11, .22]	.02	.38	[−.03, .08]	−.01	.77	[−.06, .05]
Openness	.05	.10	[−.01, .10]	.11*	.00	[.06, .17]	.00	.91	[−.06, .05]	.05	.08	[−.01, .10]
Well-being												
Health	−.02	.39	[−.07, .03]	−.04	.13	[−.09, .01]	.00	.88	[−.06, .05]	−.01	.80	[−.06, .05]
Depression	.01	.85	[−.05, .06]	.12*	.00	[.06, .18]	.05	.10	[−.01, .11]	.04	.17	[−.02, .10]
Self-esteem	.03	.28	[−.03, .09]	−.06	.05	[−.12, .00]	.00	.96	[−.06, .06]	−.03	.33	[−.09, .03]

Note. Sample 1; *N* range from 1,059 to 1,440 due to occasional missing data. *p* Values are adjusted for multiple tests. CI = confidence interval; NA = not applicable.
[a]Binary variable where female was coded as 1 and male was coded as 0.
*$p < .01$.

sensing in S2 may be due to technical issues experienced with the sensing apps used in the study. In general, passive sensing is by nature less burdensome for participants than is active logging, which requires the participant to respond to EMAs throughout the day. However, the substantial correlations between the passive sensing and active logging compliance measures across the three samples (r = .50–.83, $p < .01$; Table 5) suggest that students who complied with passive self-tracking were also more likely to comply with active tracking.

The panels in Figure 1 also show changes in compliance over time across the three samples. Panel A of Figure 1 shows an initial 2-week period of high compliance during the class assignment period followed by a steep decrease in compliance after the assignment ended, suggesting that the course credit was particularly effective as an incentive for students in the online course. For example, if we consider the 15-day class assignment period of S1 independently (an average of 66% complied with passive sensing per day and 68% complied with active logging per day), the compliance rates are comparable to those observed in S2 and S3.

Panel B of Figure 1 shows generally stable compliance rates across the two 2-week phases of the study, suggesting that shorter study durations and/or measurement burst designs may be a useful way to increase compliance. In addition, Panel B and Panel C show generally stable compliance rates that gradually decrease over time, with Panel C showing the highest compliance on average for both passive sensing and active logging. The fact that participants in S2 and S3 received monetary compensation and prize rewards for complying suggests that these incentives may increase compliance during longitudinal self-tracking studies.

Discussion

Self-tracking studies promise to provide a wealth of information about participants' experiences and behaviors gathered within the contexts of their daily lives. However, it is unclear whether potential participants would be interested in self-tracking and whether they would comply with self-tracking over an extended period of time. Here, we provide an empirical evaluation of students' interest in self-tracking and compliance with self-tracking using smartphones.

Students' Motivations to Self-Track and Participation Preferences

Overall, the results showed that 96% of students surveyed in S1 were interested in participating in self-tracking studies (i.e., only 4% of the students surveyed reported that they would not participate). Among the students surveyed, the most compelling motivation for participating was to improve academic performance (81%). The least compelling motivation was to track daily activities in a diary or journal-style format (23%). The PCA of the individual motivations revealed three broad themes for self-tracking: (1) productivity and health behaviors, (2) well-being and daily activities, and (3) campus-based social life. Overall, the base rates of endorsement were higher for the various individual motivations captured in the productivity and health behavior dimension (e.g., improve academic performance, manage daily tasks, track exercise) and the well-being and daily activities dimension (e.g., track mood, stress) than the increase in campus social life dimension (e.g., find study groups, make friends).

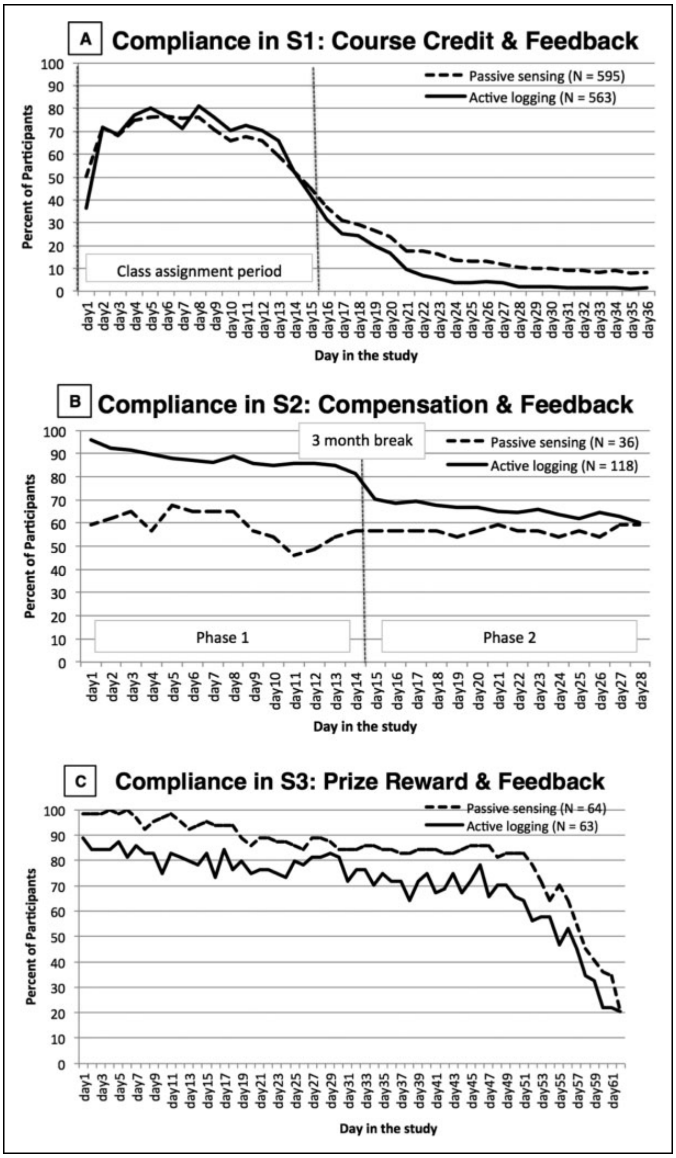

Figure 1. Compliance with passive sensing and active logging over time across the three samples: S1 (Panel A; 36 days), S2 (Panel B; 28 days), and S3 (Panel C; 61 days). (A) Compliance in S1: Course credit and feedback. (B) Compliance in S2: Compensation and feedback. (C) Compliance in S3: Prize reward and feedback.

The preferred mode of participating in self-tracking programs varied among the students. For participation via active logging, the most frequently endorsed mode of participation was responding to EMAs one or more times per day (54% of students). The least endorsed mode of participation was responding to EMAs once a semester or year (8%). For participation via passive behavioral tracking, the most frequently endorsed modes of participation were collecting data from wearable devices (48%), from online educational platforms (47%), and from smartphones (46%). The least endorsed mode of participation was collecting data from website browsing history (34%). The interitem correlations among the passive behavioral tracking preferences were all positive (r = .18–.50), indicating that students who endorsed collecting behavioral data from one source were more likely to endorse wanting to use other sources too.

These findings could be used to tailor self-tracking studies to the motivations and participation preferences of student participants. In particular, the results suggest that students who wanted to maintain productive lifestyles, monitor their well-being, and increase their campus social life were all interested in passive behavioral tracking and periodic active logging (e.g., responding to EMAs every few weeks). However, students who were motivated to monitor their well-being were also interested in daily active logging (e.g., responding to EMAs one or more times a day). Additional correlations between the individual items also revealed a high degree of specificity between motivations and participation preferences (these additional correlation tables are presented in Supplemental Table 3 of the online materials). For example, students who wanted to improve their academic performance were also interested in collecting behavioral data from their educational platforms (e.g., Canvas). Students who wanted to improve their physical health were also interested in collecting behavioral data from their wearable devices and smartphones. Students who wanted to improve their mental health were also interested in collecting data from their social media accounts and responding to EMA questions on a daily basis. By matching participants' motivations to their preferred modes of self-tracking, researchers may be able to increase compliance and maintain participants' interest in their study.

The results also revealed individual characteristics that are associated with students' interest in self-tracking, which can be used to tailor self-tracking incentives to participants' characteristics. For example, we found lower classmen were more interested in increasing their social life on campus than upper classmen. Researchers could use this information to emphasize different aspects of a study when recruiting lower classmen (e.g., participate in study to make new friends) or upper classmen (e.g., participate in study about social behavior). Personality and well-being-related traits were also associated with students' interest in self-tracking. For example, neurotic students were more interested in monitoring their well-being (e.g., tracking mood, stress) than were emotionally stable students, suggesting that neurotic students might show higher compliance rates for studies designed to track daily emotional patterns (which tend to require higher rates of EMAs to capture variability in emotional experience). Similarly, students higher in depressive symptoms were also more interested in the monitoring their well-being than were students low in depressive symptoms, suggesting that studies aiming to improve students' wellness via mobile health interventions may be successful in appealing to and recruiting student participants who may need it most.

It is likely that using such differential recruitment strategies would lead to biased samples; that is, by tailoring self-tracking studies to match participants' interests and individual characteristics, researchers may recruit samples that are not as representative as those recruited from the broader population (e.g., of students in this case) using nontailored recruitment strategies. Biased sampling would be particularly problematic for studies that aim to generalize their findings to broader populations (e.g., How does social behavior change across days of the week among college students?). To reduce such biases, studies can attempt to attract a more diverse sample by using multiple recruitment strategies (e.g., different tailored ads, multiple incentives). However, for studies with targeted research questions about specific populations (e.g., How does social behavior change across days of the week among depressed students?), this differential recruitment strategy could be quite effective in improving compliance, without limiting the generalizability of the results.

Students' Compliance With Self-Tracking Using Smartphones

Of the three studies examined here, the compliance rates showed that S2 and S3 retained the highest compliance for both passive sensing and active logging. It seems likely that the high compliance observed in these studies is due to several factors, including the use of effective incentives (monetary compensation, a Microsoft Band prize reward). The compliance rates in S1 were generally lower than those observed in S2 and S3. However, during the first 2 weeks of S1, when a relevant class assignment permitted participants to receive course credit for self-tracking, the compliance rates in S1 were comparable to those observed in S2 and S3. This finding suggests that matching the goals of self-tracking with participants' motivations (in this case, to improve academic performance) may lead to higher compliance rates among student participants. Further, the compliance trends from S1 indicate that after the opportunity for course credit ended and personal feedback was the only incentive, the rates of compliance declined steadily. Additional research adopting an experimental approach is needed to fully explain the effects of the various incentives (e.g., feedback, compensation, prizes, course credit) on compliance rates during self-tracking studies.

Limitations

One limitation of the present work concerns the generalizability of the findings to other populations. Our three samples were compromised of all college students. Thus, the motivations for self-tracking and compliance rates reported here may not generalize to other populations (e.g., middle-aged adults, the elderly). More research is needed to understand the motivations and incentives of participants recruited from different populations.

A second limitation concerns the challenge of identifying the source of noncompliance in self-tracking studies using smartphone sensing apps. For example, the discrepancy in the sample sizes across the passive sensing and active logging estimates is noteworthy because it could be due to either participants' noncompliance or a technical problem. That is, the discrepancy could be due to noncompliance behaviors, such as participants having the app installed on their phone (so it collects sensor data), but choosing not to respond to EMA prompts. Similarly, participants may comply by responding to EMA prompts, but not permit the collection of sensor data from their smartphones. However, it is also possible that the discrepancy is due to a technical problem. For example, on a given day, a participant's data may not have been uploading from their phone because their phone was off or because their phone's battery died. In such cases, the lack of incoming sensor or EMA data for that day would erroneously have been counted as a case of noncompliance.

In practice, we recommend that researchers conduct pilot studies with small samples prior to launching their full study. This approach permits a test of the tracking system to identify possible technical issues that may affect data collection (e.g., bugs in the software). One approach to handling issues with noncompliance is to monitor incoming data during the collection phase of a study, so that any noncompliant participants can be rapidly contacted to clarify the reasons for their lack of compliance. By sending compliance reminders (e.g., via e-mail, text message, phone calls) to participants during the study, researchers can address problems as they arise and encourage participation.

Conclusion

The findings presented here suggest that self-tracking tools and smartphone sensing apps in particular are viable methods for psychological research studies. The findings point to several possible directions for improving participant recruitment and retention, particularly within student samples. Future research using self-tracking tools should consider matching the study design and incentives to participants' motivations, participation preferences, and individual characteristics. Such targeted strategies could lead to higher rates of interest and compliance among participants. The degree to which targeted recruitment strategies bias samples remains to be explored; however, it appears to be a promising approach for researchers interested in tracking the daily behaviors of specific populations.

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Supplemental Material

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