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Temporal patterns of self-weighing behavior and weight changes assessed by consumer purchased scales in the Health eHeart Study

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Abstract

Self-weighing may promote attainment and maintenance of healthy weight; however, the natural temporal patterns and factors associated with self-weighing behavior are unclear. The aims of this secondary analysis were to (1) identify distinct temporal patterns of self-weighing behaviors; (2) explore factors associated with temporal self-weighing patterns; and (3) examine differences in percent weight changes by patterns of self-weighing over time. We analyzed electronically collected self-weighing data from the Health eHeart Study, an ongoing longitudinal research study coordinated by the University of California, San Francisco. We selected participants with at least 12 months of data since the day of first use of a WiFi- or Bluetooth-enabled digital scale. The sample (N = 1041) was predominantly male (77.5%) and White (89.9%), with a mean age of 46.5 ± 12.3 years and a mean BMI of 28.3 ± 5.9 kg/m^2 at entry. Using group-based trajectory modeling, six distinct temporal patterns of self-weighing were identified: *non-users* (n = 120, 11.5%), *weekly users* (n = 189, 18.2%), *rapid decliners* (n = 109, 10.5%), *increasing users* (n = 160, 15.4%), *slow decliners* (n = 182, 17.5%), and *persistent daily users* (n = 281, 27.0%). Individuals who were older, female, or self-weighed 6–7 days/week at week 1 were more likely to follow the self-weighing pattern of *persistent daily users*. Predicted self-weighing trajectory group membership was significantly associated with weight change over time ($p < .001$). In conclusion, we identified six distinct patterns of self-weighing behavior over the 12-month period. *Persistent daily users* lost more weight compared with groups with less frequent patterns of scale use.

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Conflict of interest Yaguang Zheng, Susan M. Sereika, Lora E. Burke, Jeffrey E. Olgin, Gregory M. Marcus, Kirstin Aschbacher, Geoffrey H. Tison, Mark J. Pletcher declare that he/she has no conflict of interest.

Human and animal rights and Informed consent All procedures performed in studies involving human participants were in accordance with the ethical standards of Institutional Review Board approval at UCSF and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This secondary analysis was also approved by the Institutional Review Board at Boston College. Informed consent was obtained from all individual participants included in the study. All participants provided remote, digital informed consent.

Keywords

Self-weighing; Weight change; Behavior changes; Temporal pattern

Introduction

Since overweight and obesity greatly increase risk of numerous medical conditions, including cardiovascular disease (Diaz-Melean et al., 2013), maintaining a healthy weight is important for promoting cardiovascular health. Daily self-weighing may promote attainment and maintenance of healthy weight by allowing for detection and correction of even slight weight gain and appears to contribute to long-term weight stability (Zheng et al., 2016, 2018; Carrard & Kruseman, 2016). Recently, there has been an increase in the popularity of consumer weight trackers, such as Wi-Fi or Bluetooth-enabled scales. The weight data from these scales can be synchronized with a smartphone app with features that have the ability to automatically generate summaries, graphs, and motivational messaging that can support positive behavioral change. These functions can help individuals regulate their eating and exercise behaviors, enabling users to feel more in control of their weight (Zheng et al., 2016). The automated nature of these devices increases the ease and efficiency of tracking weight (Zheng et al., 2018; Wilkinson et al., 2017).

Although increasing evidence has indicated that daily self-weighing is effective for weight loss and weight maintenance (Steinberg et al., 2015; Wing et al., 2007; Zheng et al., 2015, 2016; Madigan et al., 2015; Shieh et al., 2016), it is unclear whether this behavior is sustainable. Several studies have found that the overall pattern of self-weighing behavior tends to decline over time (Zheng et al., 2015, 2016; Steinberg et al., 2013). One study explored three distinct patterns of self-weighing for overweight/obese adults in a behavioral weight loss intervention, and found a majority of participants sustained the habit of daily self-weighing over 12 months (Zheng et al., 2016). Moreover, self-weighing may heighten negative judgments related to body image and contribute to psychological distress for some individuals (O'Neil & Brown, 2005). Additionally, the majority of reported studies used self-weighing strategies in the context of a weight loss intervention program (Steinberg et al., 2015; Wing et al., 2007; Zheng et al., 2015, 2016; Shieh et al., 2016). No prior study has reported self-weighing patterns in a natural setting outside the context of a weight loss intervention. Understanding the natural temporal patterns and factors associated with self-weighing behaviors could help clinicians, health advocates and device-developers better support individuals attempting to improve their cardiovascular health.

The Heart eHealth Study (HeH) is a prospective e-cohort study that provides a unique opportunity to examine longitudinal self-weighing behavior amongst free-living adults. HeH gathers information relevant to cardiovascular risk from a large sample of adults aged 18 years and over. A subgroup of participants who own Wi-Fi- or Bluetooth-enabled scales have connected them with their HeH Study account. HeH therefore receives objectively measured weight data from the devices but does not provide specific recommendations on use of the scale or weight management. We used 12 months of data since the day of first use of a WiFi- or Bluetooth-enabled digital scale from the HeH Study to (1) identify distinct patterns of self-weighing behavior; (2) explore factors associated with temporal self-weighing patterns; and (3) examine differences in percent weight changes by patterns of self-weighing over time. We hypothesized that three self-weighing patterns over time would be identified based on our previous work (Zheng et al., 2016): high/consistent; moderate/declined; minimal/declined.

Methods

Study design

HeH is an internet-based, direct-to-participant ongoing observational e-cohort study coordinated by the University of California, San Francisco (UCSF). Participants are invited to link data from personal health monitoring devices they might own, including Wi-Fi- or Bluetooth-enabled scales used to self-monitor their body weight. HeH does not provide recommendations on specific use of the scale or weight loss programming. Participants used scales from three manufacturers for self-weighing: the Withings Wi-Fi Body Scale (Withings-Nokia Inc., Issy-les-Moulineaux, France), the iHealth Wireless Body Analysis Scale (iHealth Lab Inc., Mountain View, CA, USA), and the Fitbit Aria Wi-Fi Smart Scale (Fitbit Inc., San Francisco, CA, USA). Participants are then able to view their self-monitoring data on their smartphone or computer, and the data are transmitted to the HeH database through application programming interfaces hosted by each device manufacturer. The HeH maintains active Institutional Review Board approval at UCSF; this secondary analysis was also approved by the Institutional Review Board at Boston College. All participants provided remote, digital informed consent.

Participants and settings

Participation in HeH is open to any adult with Internet access. Participants have been actively recruited from the UCSF cardiology and general medicine clinics, other academic institutions, lay press, social media, and through partnerships with advocacy groups and medical organizations, including the American Heart Association, and through in-app enrollment via health-related app partnerships (Dixit et al., 2016). HeH participants must be ≥ 18 years old, able to speak and read English, and have a working email address. We further restricted our study sample to HeH participants who use their own Wi-Fi- or Bluetooth-enabled scales to self-monitor their body weight and connected this device to HeH. Each participant had a full 12-month period of observation, starting from the first day they used the scale. Once users linked data with HeH, data were obtained from device servers from the date of first use (regardless of the date of linkage) until the device was no longer synced or consent to link data was withdrawn. For example, if they bought the device and started using it on May 1, but joined the HeH Study on October 1, then the analyzed first day of use would be May 1.

Measurements

Self-weighing—Data from self-weighing were transmitted from participants (via participants' mobile phones or otherwise) to cloud-based servers, and from there collected on a daily basis by HeH research servers. Using the date-stamped information, binary variables were generated for each day indicating the presence (= 1) or absence (= 0) of a recorded self-weighing measurement. Using these binary daily data, we calculated number of days of self-weighing for each week for analysis, yielding 52 aggregated weekly counts over the 12-month period for the self-monitoring of daily weight for each participant.

Weight—Objectively assessed body weight was also transmitted via Wi-Fi- or Bluetooth-enabled scales. Weekly weight was calculated by averaging daily weight data for that particular week. Weekly weight was then analyzed as the percent weight change relative to the first week of self-monitoring with the scale.

Demographic factors and medical conditions—We used age, gender, race, education, employment, income, and marital status which were self-reported at baseline by HeH participants. Body mass index (kg/m^2) was calculated based on self-reported height at baseline and objectively measured body weight on the first day use of a Wi-Fi- or Bluetooth-enabled scale. HeH also collects a wide range of self-reported medical conditions; for this analysis, we used indicators for hypertension, hyperlipidemia, diabetes, coronary artery disease, myocardial infarction, congenital heart disease, stroke, and congestive heart failure.

Statistical analysis

Descriptive statistics for continuous variables, such as percent change in weight, age, and BMI, were reported as mean ± standard deviation (SD). Categorical variables, such as gender, race, education, employment, and household income, were described using frequency counts and percentages. Statistical significance was set at .05 for two-sided hypothesis testing. Descriptive analyses were conducted using IBM® SPSS® Statistics version 25 (IBM Corp., Armonk, NY). Statistical analyses were conducted to achieve three aims.

For aim 1, group-based trajectory modeling (Nagin, 1999; Sereika et al., 2017) using PROC TRAJ in SAS version 9.4 (SAS Institute, Cary, NC) was used to identify distinct classes of trajectories of self-weighing over 52 weeks. Group-based trajectory modeling (also known as latent class growth analysis or semi-parametric finite mixture modeling) is used to identify groups of individuals following similar progressions of some behavior or outcome over age or time (Nagin, 1999). Group-based trajectory modeling assumes there are a certain number of discrete underlying groups or classes in the sample, and that each group’s trajectory has its own distinct intercept, slope and/or shape (Nagin, 1999). The predicted trajectory group membership can be used to understand the etiological underpinnings of different developmental trajectories (Jones & Nagin, 2007).

When applying group-based trajectory modeling, the dependent variable was the number of days of self-weighing per week modeled as a function of time. As the derived weekly self-weighing dependent variable to be modeled was treated as continuous variable, a censored normal model was assumed. The censored normal model is appropriate for continuous data that are approximately normally distributed, but can also be continuous type data were the observation may be censored (Jones et al., 2001). The appropriate number of trajectory groups and the shape of each trajectory for each group were determined by comparing Bayesian Information Criteria (BIC) for competing models, where models with the large negative BIC are considered to be better fitting (Nagin, 2005), as well as by visual inspection and clinical judgment considering parsimony, size, and distinctness of different trajectory groups. All data were used in determining the shape of a group's trajectory and the nonlinearity of the group's trajectory was captured through the use of polynomials of time (i.e., constant, linear, quadratic, cubic). The final model was then assessed for goodness of fit based on the average posterior probabilities for each of the subgroups (Nagin, 2005). The rules of thumb for assessing adequate fit were that each trajectory group should have an average posterior probability ≥ 0.70.

For Aim 2, the resulting predicted trajectory group membership from the final group-based trajectory model was treated as a grouping variable to examine group differences on the self-weighing frequency at week 1, demographic factors, and medical conditions. Chi-square tests of independence and general linear modeling were performed to examine the differences in demographic time-invariant categorical and continuous characteristics, respectively, among the levels of the predicted trajectory group membership. We first analyzed differences on each demographic variable and medical condition by predicted group membership using all available data. Then, the missing values for each characteristic or condition were replaced by multiple imputation, and we re-analyzed differences on each demographic variable and medical condition by the predicted self-weighing trajectory group. Non-monotone missing data patterns were identified in our data set, therefore, multiple imputation using a Markov chain Monte Carlo (MCMC) approach was used to replace missing values assuming missing at random. All demographic factors and medical conditions were included in the regression models. The missing data were imputed 10 times to generate 10 completed data sets, then each completed data set was analyzed and their results pooled for inference. We report only the pooled results in this paper.

After the crude unadjusted association for each predictor was determined, multivariate multinomial logistic regression was conducted to identify independent risk factors of self-weighing patterns. The full multivariate model was first estimated with all predictor variables, including self-weighing frequency at week 1, demographic factors, and medical conditions. Next, parsimonious models were developed applying a manual backward elimination approach by removing predictor variables sequentially from the full multivariate model. Predictor variables were removed based on the p value for the likelihood ratio Chi-square test with the p value set at .05. We repeated the same analysis after predictors with missing values were replaced by multiple imputation.

Aim 3. Random coefficient modeling with week as a within-subject continuous time variable was used to examine the difference in percent weight change (relative to weight at week 1) by self-weighing trajectory group over 52 weeks. In this analysis polynomials of time (constant, linear, quadratic and cubic) were considered. Any missing values for percent weight change were handled through modeling procedure and assumed to be missing at random. Residuals were checked and sensitivity analyses were conducted for potential outliers or influential cases identified through graphical methods. Conclusions remained unchanged when outliers were omitted; therefore, results using the full sample were reported. Then, we re-examined this association by adjusting for demographic variables (e.g., age, BMI, gender, race, education, income, status of employment, and marital status) and medical conditions as fixed effects in the random coefficient model.

Results

Demographic factors and medical conditions of participants

We identified 1041 out of 137,992 Health eHeart (HeH) Study participants with a WiFi- or Bluetooth-enabled scale who met inclusion criteria and enrolled prior to December, 2017. We compared the differences in demographic characteristics and medical conditions between individuals who were analyzed and those who were not analyzed in the HeH Study (Supplemental Table 1). The sample in this analysis was 77.5% male, the mean age was 46.5 years (SD = 12.3) and 75.8% were married or living with a partner. Most participants (89.9%) were non-Hispanic White, 77.1% had a college degree or higher, 92.8% were employed, and 64.3% had a household income > $100,000. The mean body mass index (BMI) of the sample was 28.3 kg/m^2 (SD = 5.9). The most common medical conditions were hyperlipidemia (39.5%) or hypertension (39.0%), followed by diabetes (8.6%), coronary heart disease (7.3%), congestive heart failure (3.7%), myocardial infarction (3.5%), congenital heart disease (3.5%), and stroke (3.2%). Because there were missing values for certain demographic variables and medical conditions, multiple imputation was used, which did not markedly change results from that based on only available data (Supplemental Table 2).

Adherence to self-weighing

All participants (100%) performed at least one self-weighing during the first week of scale use; however, 27.4% had stopped all scale use at 6 months and 32.7% had stopped at 12 months. More than half of the participants (56.5%) used the scales 6–7 days/week during the first week; this proportion dropped to 35.1% at 6 months and then plateaued, dropping only slightly further to 32.7% at 12 months. On average across the whole sample, self-weighing frequency declined from 5.2 days to 3.2 days/week from week 1 to week 52.

Temporal patterns of self-weighing

Through visual inspection, comparison of BIC values and clinical judgment (see Methods), we decided on a 6-group model of self-weighting trajectories, illustrated in Fig. 1 (alternate 1-, 2-, 3-, 4- and 5-group models are illustrated in Supplemental Figs. 1, 2, 3, 4, 5, along with BIC values for each model in Supplemental Table 3). The average posterior probabilities for self-weighing trajectory groups ranged from 0.97 to 0.99, well above the recommended criterion of ≥ 0.70 (Nagin, 2005), indicating adequate goodness of fit for the 6-group model. We labeled the 6 groups descriptively as *non-users* (n = 120, 11.5%), *weekly users* (n = 189, 18.2%), *rapid decliners* (n = 109, 10.5%), *increasing users* (n = 160, 15.4%), *slow decliners* (n = 182, 17.5%), and *persistent daily users* (n = 281, 27.0%).

Differences in demographic factors, self-weighing frequency for the first week and medical conditions by predicted self-weighing temporal patterns

We firstly analyzed differences among the predicted self-weighing groups in baseline demographic characteristics and medical conditions based on the available data (without imputation) (Table 1). There were significant differences in mean age by predicted self-weighing trajectory groups ($p < .001$), with older adults being more likely to follow the *persistent daily users* pattern. When the age was categorized, individuals in age ≥ 65 yeas were more likely to follow the *persistent daily users* pattern ($p = .008$). The gender distribution also differed significantly among groups ($p < .001$), with *persistent daily users* having the highest percentage of females (48.2%) compared with all other groups. No significant differences were found among self-weighing trajectory groups in terms of initial BMI, race, education, employment status, household income level and marital status. When we categorized BMI, *persistent daily users* having the highest percentage of overweight (34.3%) and obese (33.2%) conditions compared with other self-weighing patterns($p < .001$). The self-weighing frequency at week 1 was a strong predictor of subsequent self-weighing patterns; individuals who self-weighed 6–7 days during week 1 were more likely to exhibit the *persistent daily users* pattern and less likely to exhibit the *non-users* pattern, compared with those who self-weighed 1–5 days during week 1 (44.7% vs. 4.0%, 4.2% vs. 21.2% $p < .001$). Persons with congestive heart failure were more likely to demonstrate a *slow-decliners* or *non-users* pattern compared with those without congestive heart failure (*slow decliners*, 38.4% vs. 17.3%; *non-users*, 30.8% vs. 10.7%; $p = .030$). Higher percentages of individuals with coronary heart disease were *increasing users, slow decliners* and *non-users* compared with those without coronary heart disease (24.6% vs. 15.6%, 22.8% vs. 17.2%, 15.8% vs. 10.6%, respectively; $p = .045$).

We repeated the same analysis after demographic factors and medical conditions with missing values were replaced by multiple imputation. Results after imputation (Supplemental Table 4) were similar with those based on the available data without imputation. There were still significant differences in age, gender and self-weighing behavior at 1 week by self-weighing patterns; older adults, females, and those who self-weighed 6–7 days/week at week 1 were more likely to be in the *persistent daily users* group. While, there were no significant differences among predicted self-weighing trajectory groups for medical conditions, including congestive heart failure, coronary heart disease, hypertension, hyperlipidemia, diabetes, myocardial infarction, stroke and congenital heart disease.

Through multinomial logistic regression, age, gender and self-weighing behavior at week 1 were also identified as independent predictors, where older age, being female, and having self-weighed 6–7 days/week at week 1 were more likely to be in *persistent daily users* group based on both the full multivariate and final parsimonious models ($p_s < .01$) (Table 2). After missing values were replaced via multiple imputation, both gender and self-weighing 6–7 days/week at week 1 remained as significant predictors ($p_s < .001$).

Differences in percent weight changes by predicted self-weighing patterns over time

Over 52 weeks, the mean percentage of participants who had weekly weight data were 99.6% in *persistent daily users*, 92.7% in *slow decliners*, 81.9% in *increasing users*, 63.2% in *rapid decliners*, 53.6% in *weekly users*, and 11.4% in *non-users* group (only 3.3% at week 52). We found significant group differences in percent weight change by predicted self-weighing trajectory groups over time ($p < .001$) (Fig. 2). When we examined mean within-group percent change in weight over time, *rapid decliners* (estimated mean ± standard error: − 1.86 ± 0.36%), *increasing users* (− 0.80 ± 0.29%), *slow decliners* (− 1.76 ± 0.28%) and *persistent daily users* (− 1.68 ± 0.22%) had a significant weight loss ($p_s < .01$), while *non-users* (− 0.19 ± 0.39%) and *weekly users* (0.15 ± 0.27%) had no significant weight loss ($p = .638$ and $p = .578$, respectively) (Fig. 2). When we examined between-group differences in percent weight changes over time, *increasing users, non-users*, or *weekly users* had less weight loss compared with *persistent daily users* ($p_{s-} < .05$). These differences were maintained after adjusting for demographic factors and medical conditions (Supplemental Table 5). Additionally, individuals who weighed 6–7 days during the week 1 lost greater weight over time compared with those who self-weighed 1–5 days during the first week (− 1.35 ± 0.16% vs. − 0.76 ± 0.18%, $p = .013$).

Discussion

We identified six distinct patterns of self-weighing behavior using Wi-Fi- or Bluetooth-enabled scales among free-living adults who did not receive specific recommendations on scale use. The findings show a variety of distinct self-weighing patterns. Many participants stopped using the scales after a couple of months; however, approximately one-third of the participants sustained a habit of daily weighing. Consistent self-weighing was associated with weight loss over the 12-month period. We also identified a group of participants (15%) who had an increasing trend of self-weighing frequency over time.

Participants who consistently self-weighed more than 6 days/week (*persistent daily users* group) achieved greater weight loss over 12 months than other participants. Additionally, the persistent daily users group achieved higher weight loss compared to *weekly users* and *non-users* groups. This is consistent with previous studies reporting an association of daily weighing with greater weight loss and weight maintenance in those who receive behavioral weight loss interventions (Zheng et al., 2015, 2016; Steinberg et al., 2013). Our finding is also consistent with a study that examined temporal associations between weight changes and adherence or non-adherence to daily self-weighing (Helander et al., 2014), which found that weight loss took place during periods of daily self-weighing, whereas self-weighing breaks of longer than 1 month posed a risk of weight regain; they also found the greater the number of consecutive days without weighing, the greater the weight regain (Helander et al., 2014).

Our study also identified two groups with patterns of decline in self-weighing, either a decline from 6 to 1 days/week or from 6 to 4 days/week; both achieved similar weight loss compared with the *persistent daily users* group. This finding appears to differ from previous studies showing weight regain occurring with a decline in frequency of self-monitoring (Zheng et al., 2015, 2016; Burke et al., 2011). These studies, however, focused on self-weighing behavior in the context of behavioral weight loss interventions. It may be that continued frequent self-weighing behavior is less critical for weight loss maintenance when the weight loss is achieved without external motivation.

We also identified a previously undescribed group of participants (~ 15%) with increasing self-weighing frequency over time (after an initial decline in use in the first 10 weeks). Although these participants had significant weight loss over time, they did not achieve the same amount of weight loss compared to the *persistent daily user* group. Many studies have reported self-monitoring declines over time (Zheng et al., 2015, 2016; Burke et al., 2011). To our knowledge, no prior studies have reported the phenomenon of increasing self-monitoring behavior over time without interventions or incentive strategies. Our findings suggest that identification of factors that motivate this subgroup to increase self-weighing behaviors would be a fruitful area of exploration for subsequent research studies.

We found that the first week self-weighing behavior was a strong predictor of varied temporal patterns; individuals who self-weighed 6–7 days during week 1 were more likely to exhibit the *persistent daily users pattern*. We also found that participant's age and gender were different among the predicted self-weighing trajectory groups. One explanation for the age difference is that older adults are more aware of the negative health consequences of cardiovascular disease so they are more motivated to monitor their weight status. Previous work indicated that older age was a strong predictor of self-monitoring rates and other behavior changes, such as meeting weight loss and physical activity goals (Wing et al., 2004; Brokaw et al., 2015). The difference between genders regarding adherence to daily-weighing patterns might be due to females having a greater self-awareness of body image (Cameron et al., 2018). Although one weight loss study, which included a self-weighing strategy, reported a higher percentage of Asian and white individuals followed a 6–7 days/week self-weighing pattern than black individuals (Zheng et al., 2016), our study did not show any differences by race. Additionally, although congestive heart failure was not retained as an independent predictor of self-weighing patterns, persons with congestive heart failure had a trend to demonstrate a slow-decliner or non-user pattern, which might be due to sporadic scale use. They may only weigh themselves when they may be gaining fluid. Also, the reason might be due to a small sample with congestive heart failure in this analysis. To our knowledge, this is the first study to report differences in age, gender, and medical conditions for patterns of self-weighing behaviors. Future studies might aim to identify reasons why these individuals establish a certain pattern of self-weighing behavior.

The main limitation of the study is that the sample was mostly well educated, white, and male, and they self-selected into the HeH Study; however, the predominantly male sample also provides new information since most weight-monitoring studies have a small male representation. While we might expect similar patterns to emerge in other cohorts (and similar associations of those patterns with weight loss), it is likely that the relative prevalence of those patterns would be different in a more generalizable sample of the US population. None of the three brand scales provide information regarding validity, which may impact the weight outcome; only Withings scales have the function of auto-calibration. We also did not have data to confirm that the HeH participant was the sole user of the device. Additionally, the available weight data after week 10 in the non-users group were highly sporadic, resulting in weekly fluctuations in the mean weight change; and available measurements may be subject to selection bias such that average weights measured may not reflect the true average. Moreover, the causal relationship between self-weighing behavior and weight changes cannot be established with this study; self-weighing behavior could be a cause or a consequence of change in weight. Strengths of this study include the use of daily prospective data from a large free-living sample of participants who used their personal weighing scales without receiving recommendations about frequency of use, which allowed us to describe the natural temporal patterns of self-weighing behavior in the first year of use.

Additionally, our findings demonstrate that, in the absence of incentive strategies, many participants do not decrease their self-weighing frequency. In fact, we identified one group that increased self-weighing frequency, which is novel and may guide future efforts to describe the motivations and characteristics of this subgroup.

In conclusion, our work contributes to the literature related to self-weighing for weight management by describing self-weighting behaviors among a sample of participants who do not receive recommendations on specific use of scales. Six distinct patterns of self-weighing behavior were identified over 12 months. Approximately one-third of participants were able to sustain a habit of daily self-weighing and achieved greater weight loss than the other participants, even in the absence of incentive strategies.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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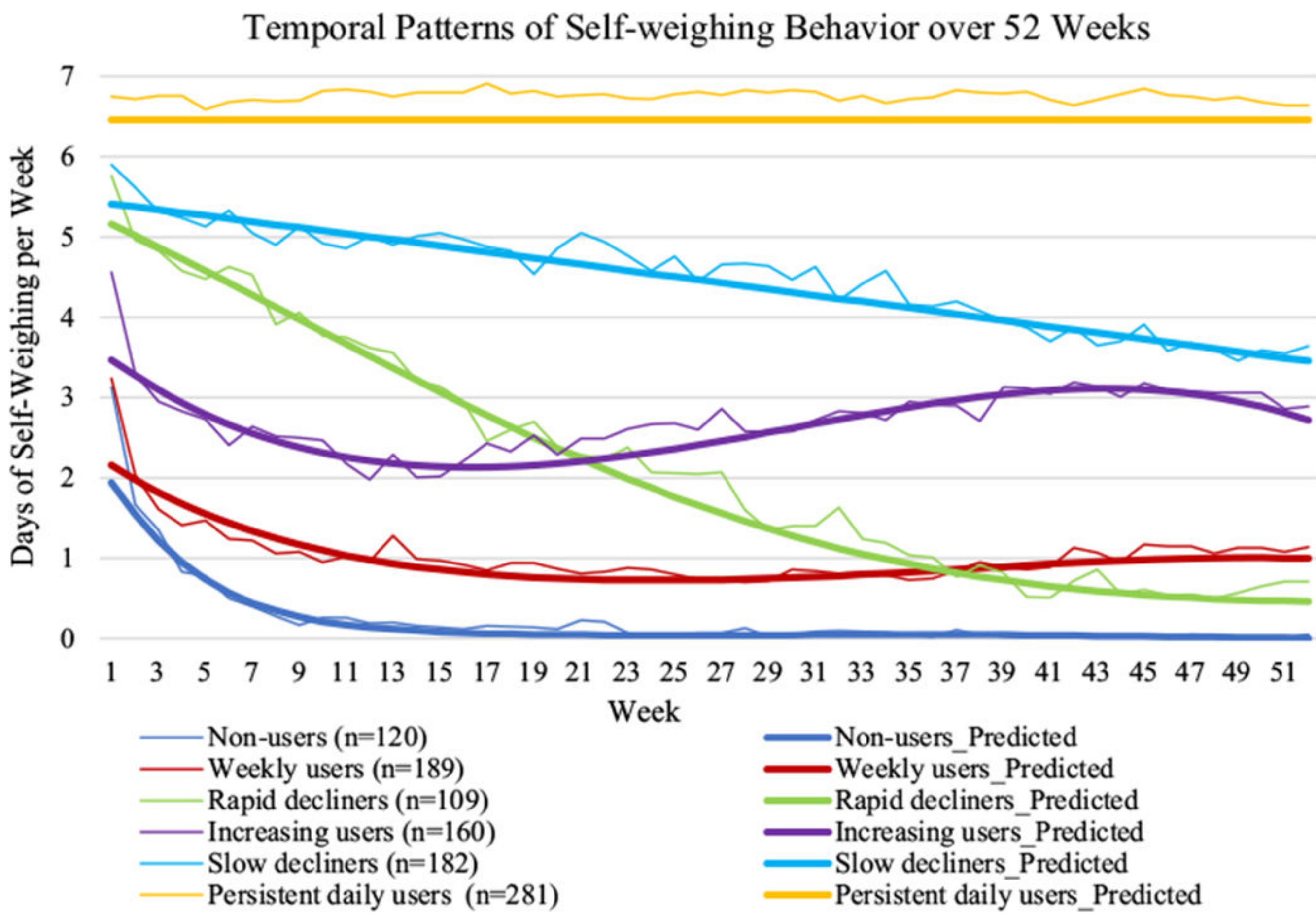

Fig. 1.
Observed and predicted temporal patterns of self-weighing behavior over 52 weeks

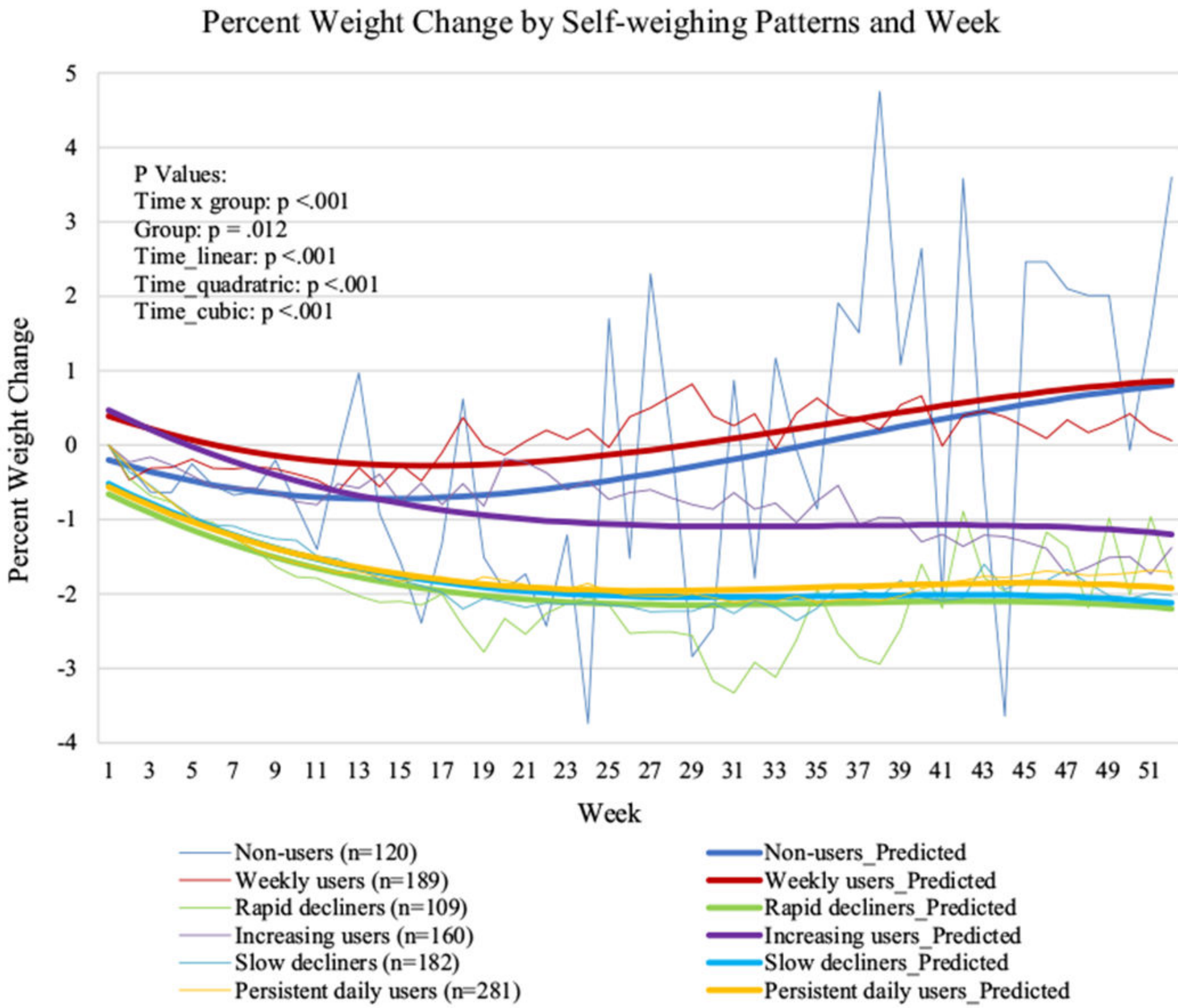

Fig. 2.

Percent weight change by self-weighing patterns and week

Table 1

Differences in demographic characteristics and medical conditions by self-weighing trajectory group (no imputation of missing values)

	n	*Non-users*	*Weekly users*	*Rapid decliners*	*Increasing users*	*Slow decliners*	*Persistent daily users*	Test statistic[a]	*p* value
Demographic characteristics									
Age, years (Mean ± SD)	1041	45.3 ± 12.1	44.7 ± 11.3	43.4 ± 11.8	45.8 ± 11.4	48.3 ± 12.5	48.7 ± 13.1	5.21	< .001
BMI, kg/m^2 (Mean ± SD)	613	29.2 ± 6.6	29.4 ± 6.4	29.3 ± 5.9	29.4 ± 6.3	27.2 ± 4.9	29.0 ± 6.5	1.76	.119
Age (n, %)								24.02	.008
< 45	479	62 (12.9)	100 (20.9)	62 (12.9)	75 (15.7)	71 (14.8)	108 (22.8)		
45–65	465	50 (10.8)	75 (16.1)	39 (8.4)	74 (15.9)	92 (19.8)	135 (29.0)		
≥ 65	97	8 (8.3)	14 (14.4)	8 (8.3)	11 (11.3)	19 (19.6)	37 (38.1)		
Weight Status (n, %)								53.23	< .001
Underweight	431	58 (13.5)	96 (22.3)	38 (8.8)	73 (16.9)	90 (20.9)	76 (17.6)		
Normal Weight	176	19 (10.8)	25 (14.2)	14 (8.0)	25 (14.2)	35 (19.9)	58 (32.9)		
Overweight	227	20 (8.8)	30 (13.2)	31 (13.7)	31 (13.7)	37 (16.3)	78 (34.3)		
Obese	207	23 (11.1)	38 (18.4)	2 (12.6)	31 (15.0)	20 (9.7)	69 (33.2)		
Gender (n, %)								75.33	< .001
Male	807	92 (11.4)	160 (19.8)	91 (11.3)	135 (16.7)	161 (20.0)	168 (20.8)		
Female	234	28 (12.0)	29 (12.4)	18 (7.7)	25 (10.7)	21 (9.0)	113 (48.2)		
Race								10.08	.073
White (non-Hispanic) (n, %)	933	103 (11.0)	170 (18.2)	98 (10.5)	148 (15.9)	155 (16.6)	259 (27.8)		
Non-White	105	17 (16.2)	18 (17.1)	10 (9.6)	12 (11.4)	27 (25.7)	21 (20.0)		
Education (n, %)								15.14	.127
≤ high school	51	8 (15.7)	13 (25.4)	7 (13.7)	8 (15.7)	6 (11.8)	9 (17.7)		
High school/college	150	23 (15.3)	24 (16.0)	19 (12.7)	21 (14.0)	18 (12.0)	45 (30.0)		
≥ College	678	63 (9.3)	113 (16.7)	68 (10.0)	108 (15.9)	121 (17.9)	205 (30.2)		
Employment (n, %)								15.02	.010
Employed[b]	822	83 (10.1)	144 (17.5)	87 (10.6)	121 (14.7)	141 (17.2)	246 (29.9)		
Unemployed	64	12 (18.8)	8 (12.5)	8 (12.5)	17 (26.5)	5 (7.8)	14 (21.9)		
Income (n, %)								14.09	.169
< 50,000	87	16 (18.4)	17 (19.5)	11 (12.6)	11 (12.6)	10 (11.6)	22 (25.3)		

	n	*Non-users*	*Weekly users*	*Rapid decliners*	*Increasing users*	*Slow decliners*	*Persistent daily users*	Test statistic[a]	*p* value
50,000 - < \$100,000	197	23 (11.7)	40 (20.3)	20 (10.2)	25 (12.7)	28 (14.2)	61 (30.9)		
≥ \$100,000	511	47 (9.2)	85 (16.6)	52 (10.2)	91 (17.8)	92 (18.0)	144 (28.2)		
Marital Status (n, %)								16.11	.007
Married or living with other	669	68 (10.2)	124 (18.5)	59 (8.9)	106 (15.8)	118 (17.6)	194 (29.0)		
Widowed, divorced, separated, other	213	26 (12.2)	28 (13.2)	36 (16.9)	30 (14.1)	27 (12.7)	66 (30.9)		
Self-weighing frequency at week 1 (times/week) (n, %)								17.75	< .001
6–7	589	25 (4.2)	30 (5.1)	76 (12.9)	66 (11.2)	129 (21.9)	263 (44.7)		
1–5	452	95 (21.0)	159 (35.2)	33 (7.30)	94 (20.8)	53 (11.7)	18 (4.0)		
Medical conditions									
Hypertension (n, %)								2.98	.702
Yes	368	37 (10.1)	69 (18.8)	40 (10.9)	62 (16.9)	57 (15.5)	103 (27.8)		
No	586	67 (11.4)	94 (16.0)	60 (10.2)	93 (15.9)	110 (18.8)	162 (27.7)		
Hyperlipidemia (n, %)								7.14	.210
Yes	375	37 (9.9)	63 (16.8)	32 (8.5)	61 (16.3)	63 (16.8)	119 (31.7)		
No	574	65 (11.4)	100 (17.4)	69 (12.0)	93 (16.2)	104 (18.1)	143 (24.9)		
Diabetes (n, %)								5.02	.414
Yes	71	10 (14.1)	16 (22.5)	8 (11.3)	7 (9.9)	9 (12.7)	21 (29.5)		
No	881	94 (10.7)	147 (16.7)	93 (10.6)	146 (16.6)	158 (17.9)	243 (27.5)		
Coronary heart disease (n, %)								11.35	.045
Yes	57	9 (15.8)	4 (7.0)	2 (3.5)	14 (24.6)	13 (22.8)	15 (26.3)		
No	895	95 (10.6)	157 (17.5)	99 (11.1)	140 (15.6)	154 (17.2)	250 (27.9)		
Myocardial infarction (n, %)								3.80	.579
Yes	30	5 (16.7)	4 (13.3)	1 (3.4)	6 (20.0)	7 (23.3)	7 (23.3)		
No	923	99 (10.8)	157 (17.0)	100 (10.8)	149 (16.1)	160 (17.3)	258 (28.0)		
Congenital heart disease (n, %)								9.94	.077
Yes	19	3 (15.8)	1 (5.3)	1 (5.3)	2 (10.5)	8 (42.0)	4 (21.1)		
No	931	101 (10.9)	161 (17.3)	99 (10.7)	152 (16.3)	158 (17.0)	260 (27.8)		
Stroke (n, %)								2.31	.805
Yes	15	1 (6.7)	3 (20.0)	1 (6.7)	1 (6.7)	4 (26.7)	5 (33.2)		
No	936	103 (11.0)	160 (17.1)	99 (10.6)	153 (16.4)	162 (17.3)	259 (27.6)		

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	n	*Non-users*	*Weekly users*	*Rapid decliners*	*Increasing users*	*Slow decliners*	*Persistent daily users*	**Test statistic**[a]	***p* value**
Congestive heart failure (n, %)								12.46	.030
Yes	13	4 (30.8)	1 (7.7)	1 (7.7)	2 (15.4)	5 (38.4)	0 (0.0)		
No	938	100 (10.7)	160 (17.1)	99 (10.6)	152 (16.2)	162 (17.3)	265 (28.1)		

SD standard deviation, *BMI* body mass index

[a]Test statistics for age and BMI was F test, test statistics for all other variables was Chi-square (X^2)

[b]Employed includes part-time and full-time employment

Table 2

Predictors of self-weighing trajectory groups using multinomial logistic regression models

Parameter	Full model			Parsimonious model		
	b	**SE**	***p* value**	**b**	**SE**	***p* value**
Age			.0004			.002
Non-users vs. *persistent daily users*	− 0.017	0.017	.331	− 0.026	0.011	.020
Weekly users vs. *persistent daily users*	− 0.030	0.016	.059	− 0.032	0.010	.002
Rapid decliners vs. *persistent daily users*	− 0.049	0.016	.002	− 0.035	0.010	.001
Increasing users vs. *persistent daily users*	− 0.034	0.015	.020	− 0.026	0.010	.008
Slow decliners vs. *persistent daily users*	0.003	0.013	.828	− 0.006	0.008	.527
Gender (ref = male)			.001			< .0001
Non-users vs. *persistent daily users*	0.4616	0.435	.289	0.688	0.313	.028
Weekly users vs. *persistent daily users*	0.9202	0.409	.024	1.359	0.313	< .0001
Rapid decliners vs. *persistent daily users*	1.0049	0.388	.010	1.202	0.305	< .0001
Increasing users vs. *persistent daily users*	0.9077	0.363	.012	1.295	0.291	< .0001
Slow decliners vs. *persistent daily users*	1.7436	0.389	< .0001	1.607	0.287	< .0001
Self-weighing frequency at week 1 (ref = 6–7 times/week)			< .0001			< .0001
Non-users vs. persistent daily users	4.6821	0.539	< .0001	3.977	0.363	< .0001
Weekly users vs. persistent daily users	5.0763	0.518	< .0001	4.354	0.348	< .0001
Rapid decliners vs. persistent daily users	2.3647	0.504	< .0001	1.920	0.355	< .0001
Increasing users vs. persistent daily users	3.2468	0.466	< .0001	3.132	0.324	< .0001
Slow decliners vs. persistent daily users	2.1980	0.485	< .0001	1.797	0.331	< .0001

Full model included all demographic factors, self-weighing frequency at week 1 and medical conditions

Parsimonious model included factors of age, gender, and self-weighing frequency at week 1

b parameter estimate, *SE* standard error