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Defining Adherence to Mobile Dietary Self-Monitoring and Assessing Tracking Over Time: Tracking at Least Two Eating Occasions per Day Is Best Marker of Adherence within Two Different Mobile Health Randomized Weight Loss Interventions

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AUTHOR CONTRIBUTIONS

G. Turner-McGrievy and C. G. Dunn conceived the project. G. Turner-McGrievy, S. Wilcox, A. Hoover, and E. Muth designed the two interventions. Data acquisition and interpretation were conducted by G. Turner-McGrievy, C. G. Dunn, A. K. Boutté, and B. Hutto. G. Turner-McGrievy and B. Hutto performed the statistical analyses. G. Turner-McGrievy and S. Wilcox provided administrative support. G. Turner-McGrievy obtained funding for the study. All authors provided critical revision of the manuscript and approved the final version.

STATEMENT OF POTENTIAL CONFLICT OF INTEREST

A. Hoover and E. Muth have formed a company, Bite Technologies, to market and sell a bite counting device. Clemson University owns a US patent for intellectual property known as "The Weight Watch," USA Patent No. 8310368, filed January 2009, granted November 13, 2012. Bite Technologies has licensed the method from Clemson University. A. Hoover and E. Muth receive royalty payments from bite counting device sales. All other authors report no potential conflict of interest.

These studies are registered at ClinicalTrials.gov: DIETMobile () 2SMART ().

Abstract

Background—Mobile dietary self-monitoring methods allow for objective assessment of adherence to self-monitoring; however, the best way to define self-monitoring adherence is not known.

Objective—The objective was to identify the best criteria for defining adherence to dietary self-monitoring with mobile devices when predicting weight loss.

Design—This was a secondary data analysis from two 6-month randomized trials: Dietary Intervention to Enhance Tracking with Mobile Devices (n=42 calorie tracking app or n=39 wearable Bite Counter device) and Self-Monitoring Assessment in Real Time (n=20 kcal tracking app or n=23 photo meal app).

Participants/setting—Adults (n=124; mean body mass index = 34.7±5.6) participated in one of two remotely delivered weight-loss interventions at a southeastern university between 2015 and 2017.

Intervention—All participants received the same behavioral weight loss information via twice-weekly podcasts. Participants were randomly assigned to a specific diet tracking method.

Main outcome measures—Seven methods of tracking adherence to self-monitoring (eg, number of days tracked, and number of eating occasions tracked) were examined, as was weight loss at 6 months.

Statistical analyses performed—Linear regression models estimated the strength of association (R^2) between each method of tracking adherence and weight loss, adjusting for age and sex.

Results—Among all study completers combined (N=91), adherence defined as the overall number of days participants tracked at least two eating occasions explained the most variance in weight loss at 6 months (R^2=0.27; P<0.001). Self-monitoring declined over time; all examined adherence methods had fewer than half the sample still tracking after Week 10.

Conclusions—Using the total number of days at least two eating occasions are tracked using a mobile self-monitoring method may be the best way to assess self-monitoring adherence during weight loss interventions. This study shows that self-monitoring rates decline quickly and elucidates potential times for early interventions to stop the reductions in self-monitoring.

Keywords

Self-monitoring; Weight loss; Adherence; Diet; mHealth

BEHAVIORAL WEIGHT-LOSS INTERVENTIONS ARE AN effective way to help people lose weight,[1] and dietary self-monitoring is considered the cornerstone of weight loss treatment.[2,3] Emerging research has examined mobile health (mHealth) technologies to help people lose weight,[4] but there is little consensus about how to objectively quantify adherence to self-monitoring and how patterns of self-monitoring may differ by mHealth methods.

Although many previous weight-loss interventions have found that frequency of dietary self-monitoring is significantly correlated with weight loss,[3,5] how these studies have defined frequency to self-monitoring has varied greatly. Examples include using day-level data (eg, the number of records completed by a participant,[6,7] whether or not anything was tracked at all on a day,[8,9] or the percentage of days at least five food or beverage items were recorded[10]), energy-level data (eg, whether a minimum number of kilocalories have been tracked each day (eg, 800 kcal)[11,12] or whether or not participants tracked at least half of a predetermined energy goal[13]), or meal-level data (when at least two meals per day were recorded[11] or percentage of days three or more meals were recorded[14]). Paper-based methods of tracking (eg, food diaries and food checklists) have been challenging to assess adherence to self-monitoring in great detail because it relied on participants to calculate energy intake by hand (generally using a calorie amounts book) and return paper forms by hand or mail.[3] Mobile methods of tracking allow for very detailed tracking that can include frequency of eating occasions or number of kilocalories recorded each day, and can be monitored remotely. Diet can be tracked using a variety of different mobile methods, such as taking pictures,[15–17] using interactive voice technology,[18] using bite-based wearable technology,[19] or using digital food databases,[5,20,21] and differing methods may require different criteria for adherence. Because mobile self-monitoring technology allows for objective assessment of self-monitoring down to very minute levels, such as number of eating occasions, when diet was recorded, or kilocalories or grams of macronutrients recorded each day, unique opportunities exist to examine patterns of tracking over time and how they might differ by varying ways of defining adherence or type of mobile tracking method. Understanding what frequency and duration of diet tracking is optimal for successful weight loss has been identified as a crucial gap in the literature around behavioral obesity treatment.[3] Therefore, the purpose of this study is to examine self-monitoring data from two different 6-month randomized weight loss studies where a total of three different mobile self-monitoring methods were used. The use of two studies, that used similar intervention methodology, allowed for a combined look at three methods vs examining the two methods used in each study separately, which helped to increase power and generalizability. The goal of this analysis is to identify the best criteria for defining self-monitoring adherence when predicting weight loss and to examine patterns of self-monitoring over the course of two 24-week studies.

MATERIALS AND METHODS

Both the Dietary Intervention to Enhance Tracking with mobile devices (DIETm)[9] and the Self-Monitoring Assessment in Real Time (2SMART)[22] studies took place at a large university located in the southeastern part of the United States and were 6-month randomized weight loss trials that each compared two different diet self-monitoring methods. Data were collected between 2015 and 2017. Both studies recruited adults classified as overweight or obese (body mass index range=25 to 49.9), who were interested in losing weight, owned a smartphone or tablet that could be used for self-monitoring, were aged 18 to 65 years, had a stable medical status (eg, no current treatment for cancer or other conditions that may influence participation), and did not have any conditions that may influence body weight (eg, no uncontrolled thyroid conditions or diabetes). Potential participants in both DIETm and 2SMART were excluded in the case that they were unable to be reached, had lost more than 10 lb during the past 6 months, had a history of an eating disorder, were currently enrolled in a weight-loss program, were unavailable during meeting times/dates, were no longer interested, or had participated in a previous weight-loss study involving podcasts. Participants were recruited through worksite listserv messages (local universities and health department), flyers, and newspaper ads. Participants completed an online screening questionnaire and were contacted via telephone to determine eligibility. Participants attended an orientation session to complete a consent form and baseline questionnaires. During the 6-month intervention, participants in both studies received a remotely delivered weight-loss intervention via twice weekly podcasts that were based on Social Cognitive Theory[23] and the Diabetes Prevention Program[24] and have been described elsewhere.[25,26] Participants had their weight measured in light street clothes without shoes using a calibrated digital scale (SECA 869, Hamburg, Germany) accurate to 0.1 kg at baseline and 6 months. Height was measured using a stadiometer (SECA 213) after participants had removed hats and shoes. The University of South Carolina Institutional Review Board approved both studies, and all participants gave written informed consent. Both studies were registered at ClinicalTrials.gov before participant enrollment (DIETm: and 2SMART:).

Participants in both studies were randomly assigned, using a computerized random-number generator, to a dietary self-monitoring method and told to use their assigned self-monitoring method throughout the entire study. The devices used in DIETm have been described elsewhere.[9] Briefly, participants in DIETm were randomly assigned to use a standard calorie-tracking app (FatSecret[27]) (App Group) or a wearable Bite Counter device (Bite Group). The Bite Counter (Bite Technologies) is a wrist-worn device that monitors intake by counting bites through the use of a micro-electromechanical gyroscope.[28] A kilocalories per bite goal (KPB) can be calculated based on baseline demographic factors, and this equation has been validated in previous work,[29] finding an average within-individual correlation between energy consumed and number of bites of 0.53,[30] with no differences in KPB among adults with normal weights or those classified as overweight or obese.[30] The FatSecret app allowed users to search for foods and beverages in a database. Participants could also scan the food barcodes for entry. The app tallied kilocalories over the course of the day to assist participants in staying within their calorie limit. The app did not provide feedback on maintaining a certain number of days in a row of self-monitoring and, in the context of both studies, was used as a way for an individual participant to assess how they were meeting their daily energy goals. Participants in 2SMART were randomized to use the FatSecret app or an app that allowed users to track foods by taking photos of foods consumed (MealLogger[31]). Photo Group participants were instructed to take pictures of everything they consumed and were trained to rate the photos as red, yellow, or green with the Traffic Light Diet.[32,33] This photo app did not provide feedback on maintaining a certain number of days in a row of self-monitoring and was used as a way for an individual participant to track how frequently they were consuming red, yellow, or green category foods. In addition, participants were asked to rate the pictures that others in the Photo Group posted as red, yellow, and green as a method of crowdsourcing group dietary feedback to individuals.[34] All groups received a personalized goal for daily intake applicable to their tracking device (eg, kilocalorie limits for the App Group; bite limit for the Bite Group; increase green foods and decrease red foods based on the Traffic Light Diet for the Photo Group).

All groups had their self-monitoring data objectively tracked over the course of 24 weeks (168 days). Because there were different methods used for self-monitoring, there were a variety of data collected over the course of both studies. Seven different adherence methods were examined that were based on both previous research studies and the commonalities of data that could be collected among the three different mHealth tracking methods. This included three methods examining adherence over the entire intervention period (number of days a participant tracked anything at all on a day, total number of eating occasions tracked, and number of days at least two eating occasions were tracked and three methods of identifying the onset of nonadherence, the number of days until participants completely ceased tracking, the last day meeting a threshold of at least 50% of upcoming days tracked, and the last day meeting a threshold of at least 25% of upcoming days are tracked). These last two methods (the last day meeting a threshold of at least 50% of upcoming days tracked and the last day meeting a threshold of at least 25% of upcoming days are tracked) examined nonadherence in a prospective manner, looking forward to compute adherence over the remaining days of the intervention. These methods examined each day prospectively and found the final day participants tracked anything before adherence to upcoming days declined to fewer than 50% or 25% of upcoming days tracked. For example, when examining Day 70 for a specific study participant, this method looks forward from Day 70 through the end of the study at day 168 (total of 99 remaining study days). In the case that a participant tracked anything for his or her diet on 40 of those 99 upcoming days (meaning 40% of upcoming days had something tracked), this would mean he or she met criteria on Day 70 for tracking more than 25% of upcoming days but would not meet criteria for tracking more than 50% of upcoming days. In addition, number of kilocalories tracked each day was tracked for the App Group and the number of bites (and calories equivalents based on their personalized KPB calculation) each day was tracked for the Bite Group. Therefore, for the Bite Group and App Group, an additional measure of adherence was examined quantified as logging a minimum of 800 kcal foods/beverages (App Group only) or 800 kcal worth of bites (Bite Group only and determined by multiplying an individual's KPB by number of bites each day). The 800 kcal cut point was used because it is often used to determine the minimal number of calories needing to be consumed to deem a day of dietary intake plausible.[12] Eating occasions were defined as having anything recorded for a meal. For example, for the MealLogger and FatSecret apps, someone could record one item for breakfast and then one item for a snack and that would be considered as two eating occasions. For the Bite Counter, a minimum of 60 minutes between records was used to differentiate eating occasions because the device did not allow users to categorize bites into meal types. For example, someone could record 30 bites between 8:00 and 8:15 AM and then 10 bites at 9:15 AM. That would be considered two eating occasions.

Statistical Analysis

For differences in baseline characteristics among the three groups and between studies, analysis of variance and independent samples *t* tests were used for continuous variables and χ^2 test of independence was used for categorical data. Descriptive statistics (mean±standard deviation) were used to describe the overall tracking of diet among all three groups and analysis of variance was used to examine differences in self-monitoring among the three groups. Sample sizes for both studies were based on a previous dietary self-monitoring intervention that examined both frequency of self-monitoring and weight loss outcomes at 6 months.[25] Two-sided tests of significance at the P=0.05 level were used.

Regression diagnostics for equality of error variances (homoscedasticity) and approximately normal distributions of residuals (Q-Q residual plot) were examined for each model. All measures except "Number of days where a threshold was met that at least 50% of upcoming days are tracked" were within conventionally accepted valid ranges. For that one measure, there was a significant heteroscedasticity finding and the Q-Q exhibited a moderate departure from linearity in the residuals. Results for that method should therefore be interpreted with caution but the remaining six methods appear to meet model assumptions adequately. Although there is no evidence of regression model assumption violations in these models, the raw weight loss variable itself is somewhat skewed. In addition, in the Photo Group, the data are sparse because just 14 participants are represented. These are still sufficient data to meet the requirements of simple linear regression models.

Strength of the association between each way of measuring adherence and the 6-month weight loss outcome was assessed with a multiple linear regression model, adjusting for age and sex. For instance, one model regressed 6-month weight loss on the total number of eating occasions tracked within the App Group, including age and sex as covariates. Separate models were repeated for each method of assessing adherence to dietary self-monitoring and for each group, as well as overall for the groups combined. The regression coefficients estimate the weight lost (in kilograms) per each unit of self-monitoring method (eg, how many kilograms lost during each day something from the diet was tracked). Note that the seven adherence criteria have a mix of three different units: dates, number of days, number of meals. To assess which method has the strongest age- and sex-adjusted association with weight change, it is necessary to use the model R^2 rather than comparing numerical values of regression coefficients based on different unit scales in the independent variables. These models were necessarily limited to study completers due to the requirement of having data on 6-month weight loss. SAS statistical software version 9.4 was used for all analyses.[35]

RESULTS

For DIETm, 81 participants completed all baseline assessments and were randomized to either the Bite Group (n=39) or App Group (n=42). Attrition (25% overall in DIETm; 23% Bite, 26% App) did not differ between groups (χ^2=0.11; P=0.75). For 2SMART, 43 participants completed all baseline assessments and were randomized to either the Photo Group (n=23) or App Group (n=20). Attrition (30% overall in 2SMART; 39% Photo, 20% App) did not differ between groups χ^2=1.89; P=0.17). Assuming no weight loss among those who did not complete the 6-month assessment (intent-to-treat carrying baseline values forward for weight), those who completed the study lost −4.4%±5.8% of their body weight compared with an assumed no change in those who did not complete from the study. Only two participants from the DIETm study identified as being Hispanic. Two additional participants in the 2SMART study were not included in final analyses due to medical reasons that could influence weight loss (eg, pregnancy and undiagnosed thyroid condition). Baseline characteristics of both the DIETm and 2SMART participants are presented in Table

1. For the present study, App Group participants from 2SMART and DIETm were combined so that there were three groups examined for the analyses: those who were randomized to use the FatSecret app (App Group; n=47 completers), those randomized to the Bite Counter (Bite Group; n=30 completers), and those randomized to use the MealLogger photo app (Photo Group; n=14 completers). There were no significant differences in baseline demographic characteristics or body mass index among the App, Bite, or Photo groups. On the 6-month questionnaire, participants were asked to report about any other weight loss methods or devices they might have used over the course of both studies and no participants reported using other methods.

Overall Tracking among the Three Groups

With all groups combined, participants used their self-monitoring method to track something on a mean 87.7±56.7 days over the course of the study or 3.6±2.4 days/week that something was tracked over 24 weeks (number of days something was tracked divided by total weeks in the study). The mean number of days per week that any tracking occurred within each group was 4.1±2.3 (95% CI 3.4 to 4.8 days) in the app group, 3.6±2.4 (95% CI 2.7 to 4.4 days) in the Bite Group, and 2.4±2.3 (95% CI 1.1 to 3.7 days) in the App Group, with the App Group logging more days than the Photo Group (P=0.047). Participants in all groups tracked a mean of 1.8±1.4 eating occasions per day. Number of eating occasions tracked per day did not differ (F=2.1; P=0.14) among the App Group (1.9±1.1, 95% CI 1.6 to 2.3), Bite Group (1.9±1.7, 95% CI 1.3 to 2.5), and Photo Group (1.1±1.3, 95% CI 0.4 to 2.1). The App Group tracked a mean of 699±406 kcal/day and the Bite Group tracked a mean of 55±35 bites/day.

Determining the Best Method to Assess Adherence to Mobile Self-Monitoring

For data examining best methods for dietary self-monitoring, only those with 6-month weight outcomes were included (N=91). The R^2 for the models predicting weight with just age and sex as covariates were R^2=0.11 (P<0.01) (all groups combined), R^2=0.19 (P<0.01) (App Group), R^2=0.15 (P=0.12) (Bite Group), and R^2=0.36 (P=0.36) (Photo Group). Table 2 shows the seven different ways dietary self-monitoring adherence was conceptualized. For all groups combined, mean±standard deviation for each method are presented, along with the R^2 for each model and the regression coefficient± standard error and P value for each examined method. The “number of days at least two eating occasions were tracked” explained the most variance in weight loss among all groups combined (R^2=0.27 [−0.09±0.02]; P<0.001). The results indicate that for every day participants tracked at least two eating occasions, they lost −0.09 kg, after adjusting for sex and age. The best predictor of weight loss differed by group. For the App Group, it was the number of days ≥800 kcal were tracked. For the Bite Group, none of the methods reached significance. For the Photo Group, it was the total number of eating occasions tracked. Those who did not complete the study at 6 months had significantly fewer days where at least two eating occasions were tracked (24.8±35.3 days) compared with those who completed the study (78.9±54.8 days; P<0.001).

Determining when Declines in Self-Monitoring Occur

Both 2SMART and DIETm were 24-week studies, which allows for an examination of when self-monitoring declines over time. Participants attended assessment visits at baseline and 6 months. DIETm had a midpoint assessment at 3 months and 2SMART had a midpoint assessment at 6 weeks, and there did not seem to be an increase in self-monitoring rates after these assessment visits. To determine when declines in self-monitoring were occurring, the final week in which the percentage of participants meeting self-monitoring adherence criteria (both combined and within each self-monitoring method) was still at least 50% (meaning at least half of participants were still meeting that particular adherence criteria) was examined. For all groups combined, the final week that at least half of participants were tracking anything with their assigned device was Week 9 (out of 24) and for tracking at least two eating occasions each day, it was Week 10. For the App Group, Week 10 was the last week at least half of participants were tracking at least 800 kcal/day. For the Bite Group, Week 3 was the last week at least half of participants were meeting their adherence criteria (examining the day on which adherence fell below 50% of upcoming days tracked). The diet adherence methods for the overall group, the App Group, and the Bite Group are all categorical. Total number of eating occasions tracked, which was the best predictor of weight loss for the Photo Group, is a continuous measure, and therefore does not allow for the examination of whether or not half of participants were meeting that criteria or not. Declines in self-monitoring are evident by examining the mean number of eating occasions tracked over the beginning, middle, and end of the study. During the first 4 weeks of the study, the Photo Group tracked a mean of 40.1±10.9 eating occasions. By Weeks 13 to 16, the mean was 10.4±3.3 eating occasions tracked and by the final 4 weeks of the study, the mean was only 6.9±4.3.

DISCUSSION

Dietary self-monitoring is a critical component of behavioral weight loss treatment.[2] Both frequent and consistent dietary self-monitoring are important for weight loss.[36,37] Most previous research examining dietary self-monitoring, regardless of self-monitoring method or adherence criteria used, shows adherence declines over time.[3,37] More recent technology-based approaches to self-monitoring have held promise as ways to make dietary self-monitoring easier, but tracking utilizing these methods still seems to decline over time.[37] Digital technologies allow for objective assessment of participant self-monitoring and can provide a variety of different data that can be used to best determine adherence.

The present study found that, when combining three different methods of mobile self-monitoring, the total number of days participants tracked at least two eating occasions was the best predictor of weight loss. This method of using a threshold for number of eating occasions tracked during the day as an adherence marker has several advantages, such as being an easy-to-define measure of adherence and a way to track adherence across very different self-monitoring modalities. In addition, this measure targets frequency, consistency, and completeness for determining adherence. However, it is important to note that all of the methods of quantifying self-monitoring adherence significantly predicted weight loss;

therefore, tracking anything may still be important to promote in future weight-loss interventions using mobile self-monitoring methods.

The best predictor of weight loss differed by group. When using a more traditional mobile self-monitoring approach where users track energy consumed each day (App Group), using a minimum of 800 kcal/day may be a better approach for determining adherence. The use of ≥800 kcal as a threshold for plausible intake is a common practice in dietary assessment research when determining whether or not reported dietary intakes are valid.[38] None of the adherence tracking methods were significant for the Bite Group. However, those methods that were more prospective, such as the number of days where a threshold was met that at least 25% or 50% of upcoming days are tracked or looking at the final day anything was tracked, explained more variance than the other examined methods. This forward-looking approach may be well suited for determining adherence for wearable technology because it indicates compliance with the several steps someone has to take to use a wearable tracking device, including remembering to charge, wear, sync, and use the device. In addition, a method that examines the percentage of upcoming days that are tracked seemed to indicate continued self-monitoring over the study period and was an important criterion for determining adherence for the Bite Group. None of the models were significant and R^2 values were low for each of the adherence methods for the Bite Group, indicating that none of the adherence methods did a robust job in explaining the variance in weight loss. Lastly, for the Photo Group, total number of eating occasions tracked was the best predictor of weight loss. With the exception of photo dietary assessment methods, which aim to quantify the nutrient content of photographed foods,[16] photo-based self-monitoring methods do not collect dietary intake data, such as energy or nutrient intake, that could be used to determine adherence. The use of recording frequency of eating occasions for determining adherence to self-monitoring can be easily applied to photo-based dietary self-monitoring methods.

The pattern of tracking was also examined over the course of 168 days. Patterns of self-monitoring demonstrated a rapid drop-off in adherence, regardless of criteria used, and point to important times when participants may be vulnerable to declining frequency of self-monitoring. Reaching participants very early on (via mobile prompting reminders, virtual coaching, or providing participants with a different preferred self-monitoring method) might help prevent more than half the sample from discontinuing self-monitoring. This pattern of decline has been demonstrated in other self-monitoring studies, showing a start in decline by Week 3 to Week 5.[37] In addition, similar to the present study, other research has found that fewer than half of participants are still meeting adherence criteria for self-monitoring by the end of the study.[3]

These findings, and the work of others,[3,37] demonstrate the need to find ways to make self-monitoring more engaging and less burdensome. Mobile technology should be leveraged to target sustained self-monitoring via reducing burden,[39,40] incentivizing use,[41–43] creating social ties,[44,45] or adding gamification.[46] However, some studies have found that users still feel tracking their diet or health behaviors with a mobile device is burdensome,[47,48] although potentially less so than traditional paper-based methods.[49] Rewarding frequency of self-monitoring through a points-based system has been shown to improve weight loss outcomes.[50] In addition, rewarding consistency of self-monitoring, or recording streaks, may be a useful strategy for improving weight-loss outcomes when using a mobile device.[36,51] One approach to increasing self-monitoring frequency could be to encourage users to try a variety of methods or regularly switch methods when noncompliance is first identified. This approach would allow users to find a method that works best for them, but could also provide novelty. Novelty may play a role in reinforcement learning and reward processing,[52] which in turn could improve adherence and engagement in a weight loss intervention. Other studies have indicated that allowing users to choose a preferred self-monitoring method may be beneficial.[15] In one 12-week weight loss study that compared the use of paper, personal digital assistant, or Web-based diary for dietary self-monitoring, participants who received their preferred self-monitoring method were significantly more adherent to tracking their diet (64.2% vs 43.4%; P=0.015) than those who didn't receive their preferred method.[11] In this study, adherence was defined as "using the diary to enter food items."[11]

The DIETm and 2SMART studies collected real-time self-monitoring data that allowed for objective tracking over the course of 168 days. As evidenced by these studies, both the pattern of rapid decline in dietary self-monitoring and use of real-time data collection highlight the need to use adaptive intervention designs to quickly assess who needs a different self-monitoring approach or activation of adherence strategies.[53,54]

The present study has several strengths. The study defined adherence through the use of objectively measured self-monitoring data and body weight over the course of 24 weeks. In addition, three different mobile dietary self-monitoring methods were assessed, which helps to increase the generalizability of these findings to multiple methods of self-monitoring. The study also has limitations. The attrition rate was between 25% to 30% in the two studies; however, this is similar to what has been observed in several other remotely delivered weight-loss interventions[55–57] and attrition rates did not differ between groups or studies. The study sample was also mostly highly educated, white women, which may limit generalizability.

CONCLUSIONS

Mobile dietary self-monitoring methods hold promise as a way to provide users with a lower-burden approach to tracking diet and to allow researchers to objectively track use in real time. Defining adherence to self-monitoring for mobile methods of tracking may differ from previous studies using nonmobile methods. The present study found that using the criteria of number of days at least two eating occasions were tracked best predicted weight loss at 6 months when examining three different mHealth tracking methods combined. Researchers who use novel mobile diet self-monitoring technologies should continue to assess measures of adherence as part of ongoing efforts to improve interventions. This study also demonstrated that even with the use of mobile methods, there were rapid declines in adherence rates over time. Future research should examine whether or not including additional components to enhance engagement and reduce user burden can help sustain self-monitoring for longer.

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RESEARCH SNAPSHOT

Research Question

What are the best criteria for defining self-monitoring adherence when predicting weight loss among adults and how do patterns of self-monitoring use over the course of two 24-week studies change over time?

Key Findings

The best dietary self-monitoring adherence criteria to use in weight loss studies using mobile health technology may be the total number of days at least two eating occasions are tracked. This study shows that self-monitoring rates decline quickly and elucidates potential times for early interventions to stop the reductions in self-monitoring.

Table 1.

Baseline demographic characteristics of participants in two remotely delivered weight loss interventions (Dietary Intervention to Enhance Tracking with mobile devices [DIETm] and Self-Monitoring Assessment in Real Time [2SMART]) using mobile dietary self-monitoring modalities;Columbia, SC (2015–2017)

Characteristic	DIETm	2SMART
n	81	43
	mean±standard deviation	
Age (y)	48.1±11.9	42.4±12.4
Body mass index	34.7±5.6	34.5±5.7
	n (%)	
Sex		
Female	67 (83)	39 (91)
Male	14 (17)	4 (9)
Race		
Black	14 (17)	7 (16)
White	66 (82)	35 (82)
Other	1 (1)	1 (2)
Education		
High school or some college	12 (15)	9 (21)
College graduate	37 (46)	13 (30)
Advanced degree	32 (39)	21 (49)
Marital status		
Married	50 (62)	26 (61)
Partnered/living with someone	5 (6)	4 (9)
Single	20 (25)	10 (23)
Divorced	6 (7)	3 (7)

Table 2.

Regression coefficients and variance explained from 6-month weight loss regressed on seven self-monitoring adherence criteria with three different mobile dietary self-monitoring methods, both combined and alone

	All Groups Combined (n = 91)		App (n = 47)	Bite (n = 30)	Photo (n = 14)
Measure of adherence to dietary self-monitoring	**Mean±standard deviation**	**R^2 for overall model[a] (Regression coefficient±standard error; *P* value for examined method)[b]**			
No. of days anything was tracked for diet	87.7±56.7	0.25 (−0.08±0.02; *P*=0.001)	0.33[*] (−0.10±0.04; *P*<0.01)	0.18 −0.03±0.03; *P*=0.32)	0.48 (−0.09±0.04; *P*=0.03)
Total no. of eating occasions tracked	299.6±226.4	0.21 (−0.02±0.10; *P*<0.01)	0.37[*] (−0.03±0.001; *P*=0.001)	0.15 (−0.0009± 0.007; *P*=0.89)	0.60[*] (−0.03±0.01; *P*<0.01)[c]
No. of days at least 2 eating occasions were tracked	78.9±54.8	0.27 (−0.09±0.02; *P*<0.001)[c]	0.34[*] (−0.11±0.04; *P*<0.01)	0.17 (−0.03±0.04; *P*=0.44)	0.50 (−0.10±0.04; *P*=0.03)
The no. of days until participants completely ceased tracking	117.4±56.2	0.21 (−0.07±0.02; *P*=0.001)	0.26[*] (−0.08±0.04; *P*=0.06)	0.22 (−0.05±0.03; *P*=0.14)	0.44 (−0.08±0.04; P=0.05)
The last day meeting a threshold of at least 25% of upcoming days are tracked	87.8±74.9	0.23 (−0.06±0.03; *P*<0.001)	0.30[*] (−0.07±0.03; *P*=0.01)	0.21 (−0.04±0.03; *P*=0.15)	0.45 (−0.06±0.03; *P*=0.048)
The last day meeting a threshold of at least 50% of upcoming days tracked	70.7±77.1	0.25 (−0.07±0.02; *P*<0.001)	0.33[*] (−0.07±0.02; *P*<0.01)	0.22 −0.04±0.02; *P*=0.14)	0.53[*] (−0.08±0.03; *P*<0.01)
No. of days at least 800 kcal or 800 kcal equivalent of bites were tracked (App and Bite groups only)	73.5±49.0	0.27 (−0.09±0.03; *P*=0.001)	0.38[*] (−0.13±0.04; *P*<0.001)[c]	0.15 (−0.001 ±0.04; *P*=0.98)	N/A[d]

[a]All models were adjusted for age and sex.

[b]Weight lost (in kilograms) for change in each unit of self-monitoring method after adjustment for age and sex. For example, for the self-monitoring adherence measure of "No. of days anything was tracked for diet," participants lost −0.08 kg for each unit change in that method (ie, each day anything each tracked).

[c]The dietary tracking adherence method that best explained the variance in and had the strongest association with weight loss.

[d]N/A=not applicable.

[*]Significant at the *P*<0.05 level.