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RESEARCH ARTICLE

Patterns of Engagement With an Application-Based Dietary Self-Monitoring Tool Within a Randomized Controlled Feasibility Trial

Melissa C. Kay, PhD,[1,2] Hailey N. Miller, PhD,[2,3] Sandy Askew, MPH,[2] Erin M. Spaulding, PhD,[4,5] Miriam Chisholm, BS,[2] Jacob Christy, MS,[2,6] Qing Yang, PhD,[3] Dori M. Steinberg, PhD.[3,7]

Introduction: The Dietary Approaches to Stop Hypertension dietary pattern is a proven way to manage hypertension, but adherence remains low. Dietary tracking applications offer a highly disseminable way to self-monitor intake on the pathway to reaching dietary goals but require consistent engagement to support behavior change. Few studies use longitudinal dietary self-monitoring data to assess trajectories and predictors of engagement. We used dietary self-monitoring data from participants in Dietary Approaches to Stop Hypertension Cloud (N=59), a feasibility trial to improve diet quality among women with hypertension, to identify trajectories of engagement and explore associations between participant characteristics.

Methods: We used latent class growth modeling to identify trajectories of engagement with a publicly available diet tracking application and used bivariate and regression analyses to assess the associations of classifications of engagement with participant characteristics.

Results: We identified 2 latent classes of engagement: consistent engagers and disengagers. Consistent engagers were more likely to be older, more educated, and married or living with a partner. Although consistent engagers exhibited slightly greater changes in Dietary Approaches to Stop Hypertension score, the difference was not significant.

Conclusions: This study highlights an important yet underutilized methodologic approach for uncovering dietary self-monitoring engagement patterns. Understanding how certain individuals engage with digital technologies is an important step toward designing cost-effective behavior change interventions.

Trial registration: This study is registered at www.clinicaltrials.gov NCT03215472.

From the [1]Department of Pediatrics, Duke University, Durham, North Carolina; [2]Duke Global Digital Health Science Center, Duke University, Durham, North Carolina; [3]School of Nursing, Duke University, Durham, North Carolina; [4]Welch Center for Prevention, Epidemiology, and Clinical Research, Johns Hopkins University School of Medicine, Baltimore, Maryland; [5]Digital Health Innovation Laboratory, Ciccarone Center for the Prevention of Cardiovascular Disease, Division of Cardiology, Department of Medicine, Johns Hopkins University School of Medicine, Baltimore, Maryland; [6]Medable, Inc., Palo Alto, California; and [7]Equip Health, Inc., Carlsbad, California

Address correspondence to: Melissa C. Kay, PhD, Duke Global Digital Health Science Center, Duke University, 417 Chapel Drive, Campus Box 90086, Durham NC 27708. E-mail: melissa.kay@duke.edu.

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INTRODUCTION

The Dietary Approaches to Stop Hypertension (DASH) dietary pattern is an important part of national blood pressure (BP) and dietary guidelines for Americans.[1] It has shown proven results for a variety of disease risk factors, including hypertension, excess weight, and other cardiometabolic disorders.[2–6] However, adherence to the DASH dietary pattern remains low,[7] as evidenced by most Americans with hypertension exhibiting uncontrolled BP.[8] Thus, intensified efforts are needed to support Americans' adherence to the DASH dietary pattern. In response, we created DASH Cloud, a feasibility trial utilizing application (app)-based dietary self-monitoring to support adherence to the DASH dietary pattern.[9]

DASH Cloud focused on dietary self-monitoring because it is one of the most successful tools for managing dietary intake.[10] Digital technologies, such as smartphone apps, can be used to support dietary self-monitoring and subsequent behavior change, particularly among people with chronic conditions.[11,12] Dietary self-monitoring apps allow people to report dietary intake in real time and with ease; they offer an accessible platform for dietary data entry and provide immediate feedback for evaluation of one's progress toward goals, another effective strategy for behavior change.[13,14] However, for an app to be effective, one must use it[15]; meaning that to adopt the DASH dietary pattern, one must first self-monitor dietary intake. This successful utilization is often referred to as engagement.[16] *Engagement* is defined in a variety of ways depending on the discipline.[17] For the purposes of this study, we refer to *engagement* on the basis of the frequency of usage and define *engagement* as the usage of an app to self-monitor one's daily dietary intake.[18]

Poor engagement is commonly observed with smartphone apps, contributing to their insufficiency for sustaining behavior change, and evidence is lacking regarding the main factors contributing to this problem.[19,20] In addition, studies assessing the relationship between user engagement and dietary self-care behaviors for the prevention of cardiovascular disease are limited.[21] Furthermore, few studies identify distinct engagement trajectories, which may be helpful to characterize and predict engagement patterns and make digital behavior change interventions more effective.[16] Latent class growth modeling offers a way to identify individuals with similar patterns of engagement when repeated measurements are available.[22,23] Latent class growth modeling can be used for exploratory purposes to uncover trajectories within the population, which could help identify individuals who do not respond to behavior change interventions. Finally, given concerns around inequalities in app usage,[24,25] it's important to identify patterns of engagement across sociodemographic characteristics that may be related to higher app usage.

The objectives of this project were to (1) identify dietary self-monitoring engagement patterns using latent class growth modeling and (2) examine the associations between personal characteristics and dietary self-monitoring engagement patterns among those participating in DASH Cloud, a 3-month randomized controlled feasibility trial utilizing a commercial diet-tracking smartphone app. We also explored the relationship between engagement patterns and 3-month change in DASH adherence score.

METHODS

Study Sample

The design and primary results of DASH Cloud have previously been published.[9] In brief, DASH Cloud was a parallel-group randomized controlled feasibility trial comparing app-based diet tracking (active comparator) with app-based diet tracking plus a digital behavior change intervention, including tailored feedback through text messages about adherence to DASH and motivational messages designed to support behavior change. Women were eligible to participate if they were aged between 21 and 70 years, had a BMI >18.5 kg/m^2, self-reported being diagnosed with hypertension, were on medication for BP, or had a recent systolic BP measurement of 120–159 mmHg or a diastolic measurement of 80–99 mmHg. Participants had to own a smartphone and be willing to receive daily text messages. Eligible participants were randomized to 1 of 2 study arms using a permuted block randomization scheme. All study protocols were in accordance with the ethical standards of Duke University and were approved by the Duke University Health Center IRB. The study was registered on ClinicalTrials.gov on July 12, 2017 (NCT03215472).

Participants in both study arms of DASH Cloud were asked to self-monitor their daily dietary intake using the commercially available diet-tracking smartphone app, Nutritionix (Syndigo LLC). Nutritionix is the largest verified database of nutrition information and is maintained by a team of registered dietitians. DASH Cloud integrated with Nutritionix using an app-programming interface. Through sophisticated algorithms, DASH Cloud used the dietary-tracking data collected from Nutritionix to calculate a DASH score on the basis of daily consumption. This DASH adherence score was calculated using the Mellen et al.[26] index. The Mellen et al.[26] index uses a 9-point scale on the basis of the previous day's intake for potassium, sodium, magnesium, calcium, saturated fat, total fat, total protein, cholesterol, and fiber. Our algorithm compared the total reported intake in Nutritionix with the recommended targets for these nutrients in the DASH dietary pattern as reported in Mellen et al.[26] Using our software platform, each nutrient was assigned a score on the basis of its difference from the recommended target (1=met target, 0.5=met intermediate target, 0=did not meet target) (Table 1). Scores for each nutrient were summed for a total DASH adherence score. Participants in the intervention group received (up to) daily text messages providing feedback and tips on the basis of their DASH adherence

Table 1. Scoring Methodology for Adherence to the DASH Dietary Pattern by Mellen et al.[26]

Component	DASH score target	Intermediate target
Dietary components for which greater intakes receive higher scores		
Protein, g	18% of total daily kcal	16.5% of total daily kcal
Fiber, g	14.8 g/1,000 kcal per day	9.5 g/1,000 kcal per day
Magnesium, mg	238 mg/1,000 kcal per day	158 mg/1,000 kcal per day
Calcium, mg	590 mg/1,000 kcal per day	402 mg/1,000 kcal per day
Potassium, mg	2,238 mg/1,000 kcal per day	1,534 mg/1,000 kcal per day
Dietary components for which lower intakes receive higher scores		
Total fat, g	27% of total daily kcal	32% of total daily kcal
Saturated fat, g	6% of total daily kcal	11% of total daily kcal
Cholesterol, mg	71.4 mg/1,000 kcal per day	107.1 mg/1,000 kcal per day
Sodium, mg	2,400 mg per day	3,000 mg per day

DASH, Dietary Approaches to Stop Hypertension.

score from the previous day. At 3 months, both study arms saw a small increase in DASH adherence; adding a digital behavioral change intervention to a diet tracking app did not increase DASH adherence compared with diet tracking alone.[9]

Measures

Participant demographics, psychosocial characteristics, and other health-related behaviors were assessed through an online survey before their in-person assessment using the Research Electronic Data Capture Project (REDCap) web application. Table 2[27–31] briefly summarizes the survey measures used in the current analysis.

Height, weight, and BP were measured by our study staff at baseline and the 3-month in-person assessment. Full details of the data collection protocol have been previously published.[9]

To assess change in adherence to the DASH dietary pattern, participants were asked to complete two 24-hour dietary recalls at baseline and 3 months using the Automated Self-Administered 24-hour (ASA24) recall tool from the National Cancer Institute.[32] The ASA24 is an automated tool that uses the U.S. Department of Agriculture's validated multiple pass method to assess dietary intake for a 24-hour period.[32] Participants completed 1 weekend day and 1 weekday of dietary intake within a 2-week period. The data were used to calculate adherence to the DASH dietary pattern using the scoring methodology defined by Mellon and colleagues.[26] Nutrient targets can be found in Table 1. Individual nutrient scores were summed to calculate a total DASH adherence score. The score range is 0–9, with higher scores indicative of greater adherence and a score of 9 indicating full adherence to the DASH dietary pattern.

The main outcome of this analysis was *engagement with the dietary tracking app* (i.e., *self-monitoring*), which was operationally defined as the percentage of days each week a participant tracked their dietary intake in Nutritionix. Days in which a participant logged <600 or >3,500 calories were considered invalid tracking completions.[33]

Statistical Analysis

Participants' baseline demographic, clinical, health behavior, and psychological characteristics were summarized using descriptive statistics. We used latent class growth analysis to identify distinct engagement trends within our participant sample. To facilitate the model selection process and explore overall trends in engagement, we produced empirical summary plots of weekly engagement over the 12-week intervention. We also produced panels of individual profile plots (spaghetti plots) to examine the underlying heterogeneity in patterns of changes in engagement. On the basis of the

Table 2. Survey Measures and Descriptions Administered in the DASH Cloud Feasibility Trial

Construct	Measure description
Medication adherence	Two items from the measure developed by Voils et al.[27] were used to determine medication adherence over the past 7 days: "I missed or skipped at least one dose of my blood pressure medication," and "I was not able to take all of my blood pressure medication." Participants who reported never for both items were classified as adherent.
Physical activity	The GPAQ, an 18-item measure developed by the WHO, estimates time spent doing moderate–vigorous physical activity in a typical week and classifies respondents by adherence to WHO's recommendations for physical activity.[28]
Text messaging frequency	Participants were asked several questions related to their use of smartphones and the internet previously used by the Pew Research Center.[29,30]
Depressive symptoms	The PHQ-8 is an 8-item measure used to diagnose depressive symptoms in general populations.[31] A threshold of 5 indicates mild symptoms, 10 suggests moderate symptoms, and 15—24 indicates severe depressive symptoms.

DASH, Dietary Approaches to Stop Hypertension; GPAQ, Global Physical Activity Questionnaire; PHQ-8, Patient Health Questionnaire-8.

continuous operationalization of engagement in dietary tracking, we used a censored normal (CNORM) distribution option to model the outcome.[34] On the basis of the different types of engagement observed in individual profile plots, we built latent class models with 2 and 3 classes. We also included possible polynomial order in time (e.g., linear and quadratic) to account for the different time trends in the classes. We compared these models for fit on the basis of visual inspection, Akaike Information Criteria, and Bayesian Information Criteria. We also calculated relative entropy, an averaged posterior probability of group membership to evaluate classification quality. On the basis of the interpretation of the subgroups, the percentage of the sample in each subgroup, the classification quality of the model, and the model fit indices, we determined the optimal number of latent classes for our analysis was 2.[35,36]

We explored the associations between participant characteristics and engagement class membership (engagement groups) using bivariate analysis. Pearson chi-square tests were conducted for most categorical variables, but if the expected cell size was <5, we alternatively used Fisher's exact tests. We conducted *t*-tests to compare group means for continuous variables. We also calculated the OR for categorical variables and least square means for continuous variables to show effect sizes.

Change in DASH score adherence between baseline and 3 months was compared between engagement groups using repeated-measures ANOVA. Participants who failed to complete 3-month ASA24 surveys or who reported invalid caloric intakes <600 kcal or >3,500 kcal on the dietary assessment had missing DASH adherence scores at 3 months; these missing values were addressed in the analysis of change using maximum likelihood methods.

All data management, descriptive analysis, bivariate analysis, and regression models were conducted in SAS 9.4 (SAS Institute, Cary, NC). Proc Traj, a stand-alone SAS macro was used for constructing the latent class growth analysis.[34] Because our analysis was exploratory in nature, all tests used an α level of 0.05, and we did not adjust for multiple testing. All *p*-values were 2 sided.

RESULTS

Our sample of women was on average aged 49.9 ($\pm$11.9) years. The majority were non-Hispanic White (69.5%), were married/living with a partner (66.1%), and had a 4-year college degree or higher education (83.1%) (Table 3). Over two thirds of participants had a baseline BP that was elevated or hypertensive, with over half of the sample classified as hypertensive (58.0%). Most of the women had obesity (71.2%); the average BMI was 33.8$\pm$7.6 kg/m^2. All participants were employed and owned a smartphone for >2 years, and nearly everyone reported using their cell phone often (96.6%), sending text messages often (83.1%), and using apps on their smartphone (98.3%).

We did not observe the study arm to be a significant predictor of the engagement group, with 52.8% of the control group and 47.2% of the intervention group classified as consistent engagers (p=0.49). Thus, we present results from the whole sample. Figure 1 shows the overall engagement trajectory of the full sample. Average engagement over the course of the study was 63.4% (SD=42.3%) or 4.4 days per week, with weekly averages ranging from 42.4% to 91.3% or from 3.0 to 6.4 days per week. The trajectory of the weekly averages is characterized by a steady decline over the course of the study.

The 2 latent classes of engagement identified in the 2-class model were consistent engagers (n=36) and disengagers (n=23). Figure 2 shows the overall engagement trajectory by engagement group. The consistent engagers group had a higher average weekly engagement (range=68.3%, 97.6%) and a slower linear decline over time (β= −5.9; p<0.0001). The disengagers group experienced more variability in average weekly engagement (range=0.0%, 81.4%) and a much more rapid decline in engagement (β= −31.7; p<0.0001) that curved over time (β=1.2; p=0.005).

The results of our bivariate analysis of participant characteristics by engagement groups are presented in Table 3. We observed a statistically significant difference in age between the latent classes: consistent engagers were on average older than disengagers (mean$\pm$SD: 52.4$\pm$11.9 vs 46.0$\pm$11.1; least square mean difference: 6.4 [0.2, 12.6]; p=0.04). Consistent engagers were also more educated, with 91.7% having a college degree or above compared with 69.6% of the disengagers (OR=4.7; 95% CI=0.9, 31.8; p=0.04). Being married or living with a partner was also more common among consistent engagers (77.8% vs 47.8% of disengagers; OR=3.8; 95% CI=1.2, 11.9; p=0.02). No other comparisons were statistically significant.

Figure 3 shows that consistent engagers had a greater improvement in their DASH adherence scores from baseline to 3 months with less within-group variability (mean$\pm$SD: 1.0$\pm$1.1 vs 0.3$\pm$1.8). However, the difference in change between groups was not statistically significant (estimated mean difference=0.6; 95% CI= −0.2, 1.4; p=0.17).

DISCUSSION

For this study, we used objective app data and latent class growth modeling to identify 2 different trajectories of engagement with a dietary tracking app among a sample of women with high blood pressure. Women were classified as consistent engagers or disengagers. Many studies note the decrease in the use of smartphone apps over time, highlighting the importance and yet significant challenge of building sustained user engagement.[37–39] However, few studies highlight different patterns of engagement across time when participating in digital dietary change interventions.[40,41] Instead, many

Table 3. Sociodemographic and Clinical Baseline Characteristics of Participants Enrolled in the DASH Cloud Feasibility Trial and Associations With Engagement Class (N=59)

Characteristics or category	Total, *N* (%) or mean ± SD	Consistent engagers, *n* (%) or mean ± SD	Disengagers, *n* (%) or mean ± SD	OR (95% CI) or LS mean difference, (95% CI)	*p*-value
Demographics					
Age, years	49.9 ± 11.9	52.4 ± 11.9	46.0 ± 11.1	6.4 (0.2, 12.6)	0.04
Education					
Less than a college degree	10 (16.9)	3 (8.3)	7 (30.4)	ref	0.04
College degree or above	49 (83.1)	33 (91.7)	16 (69.6)	4.7 (0.9, 31.8)	
Race/ethnicity					
Non-Hispanic White	41 (69.5)	26 (72.2)	15 (65.2)	ref	0.78
Non-Hispanic Black	10 (16.9)	5 (13.9)	5 (21.7)	0.6 (0.1, 3.0)	
Other	8 (13.6)	5 (13.9)	3 (13.0)	1.0 (0.2, 7.1)	
Married/living with partner					
No	20 (33.9)	8 (22.2)	12 (52.2)	ref	0.02
Yes	39 (66.1)	28 (77.8)	11 (47.8)	3.8 (1.2, 11.9)	
Children living in household					
None	33 (58.9)	19 (54.3)	14 (66.7)	ref	0.36
≥1	23 (41.1)	16 (45.7)	7 (33.3)	1.7 (0.5, 5.2)	
Insurance					
Medicaid, Medicare, or none	11 (18.6)	7 (19.4)	4 (17.4)	ref	1.00
Private insurance	48 (81.4)	29 (80.6)	19 (82.6)	1.1 (0.2, 6.1)	
Anthropometric and clinical measurements					
BMI classification					
Healthy (18.5 to <25 kg/m^2)	7 (11.%)	4 (11.1)	3 (13.0)	ref	0.12
Overweight (25.0 to <30 kg/m^2)	10 (16.9)	9 (25.0)	1 (4.3)	0.9 (0.1, 6.2)	
Obese (30 kg/m^2 or higher)	42 (71.2)	23 (63.9)	19 (82.6)	6.0 (0.4, 392.7)	
Blood pressure classification[a]					
Normal (SBP <120 mmHg and DBP <120 mmHg)	18 (32)	11 (31.4)	7 (31.8)	ref	0.62
Elevated (120 ≤ SBP < 130 mmHg and DBP <80 mmHg)	6 (11)	5 (14.3)	1 (4.5)	3.0 (0.3, 171.6)	
Hypertensive (SBP ≥130 mmHg or DBP ≥80 mmHg)	33 (58)	19 (54.3)	14 (63.6)	0.9 (0.2, 3.2)	
Health-related behaviors					
Dietary intake, DASH score	2.3 ± 1.3	2.3 ± 1.2	2.2 ± 1.4	0.1 (−0.7, 0.8)	0.85
Currently taking blood pressure medication					
No	30 (50.8)	17 (47.2)	13 (56.5)	ref	0.49
Yes	29 (49.2)	19 (52.8)	10 (43.5)	1.5 (0.5, 4.2)	
Medication adherence[b]					
Nonadherent	8 (29)	3 (16.7)	5 (50.0)	ref	0.09
Adherent	20 (71)	15 (83.3)	5 (50.0)	4.7 (0.6, 42.3)	
Meets physical activity recommendations					
No	30 (51.7)	15 (42.9)	15 (65.2)	ref	0.10
Yes	28 (48.3)	20 (57.1)	8 (34.8)	2.5 (0.8, 7.4)	
Text messaging frequency					
Often	49 (83.1)	27 (75.0)	22 (95.7)	ref	0.07
Sometimes/rarely/never	10 (16.9)	9 (25.0)	1 (4.3)	7.1 (0.9, 335.7)	
Depressive symptoms					
Less than mild	37 (62.7)	24 (66.7)	13 (56.5)	ref	0.43
Mild or greater	22 (37.3)	12 (33.3)	10 (43.5)	0.7 (0.2, 1.9)	
High	30 (50.8)	19 (52.8)	11 (47.8)	1.2 (0.4, 3.5)	

[a]Participants (n=2) did not have a blood pressure measurement because of monitor malfunction (n=1) and poor fitting cuff (n=1).
[b]Medication adherence was compared among participants who reported currently taking blood pressure medication only. One participant did not complete the medication adherence questionnaire.
DASH, Dietary Approaches to Stop Hypertension; DBP, diastolic blood pressure; SBP, systolic blood pressure.

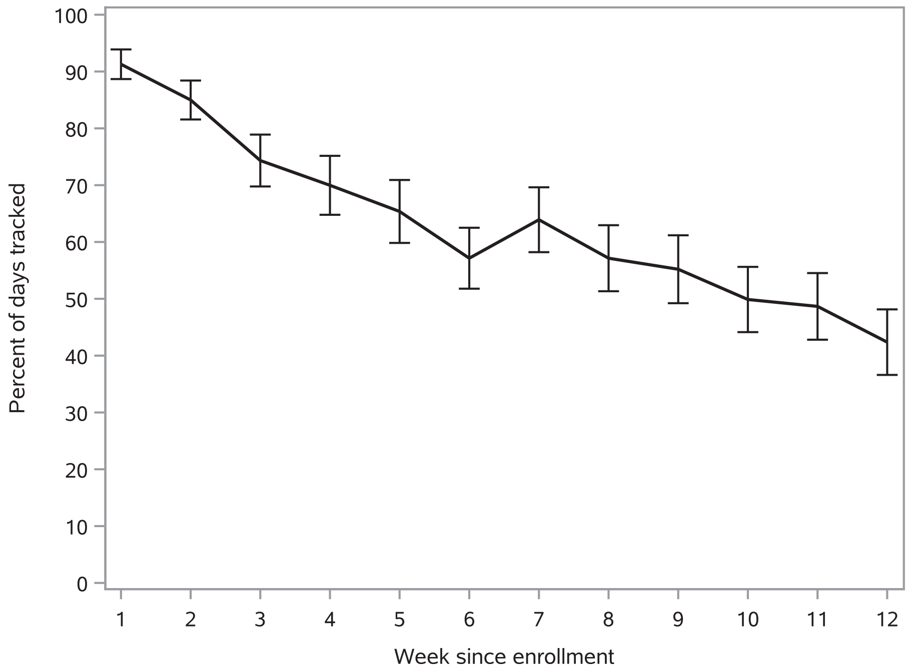

Figure 1. Empirical summary plot of weekly engagement with dietary tracking using a smartphone application over 3 months in the full DASH Cloud sample (mean±1 SE).

DASH, Dietary Approaches to Stop Hypertension; SE, standard error.

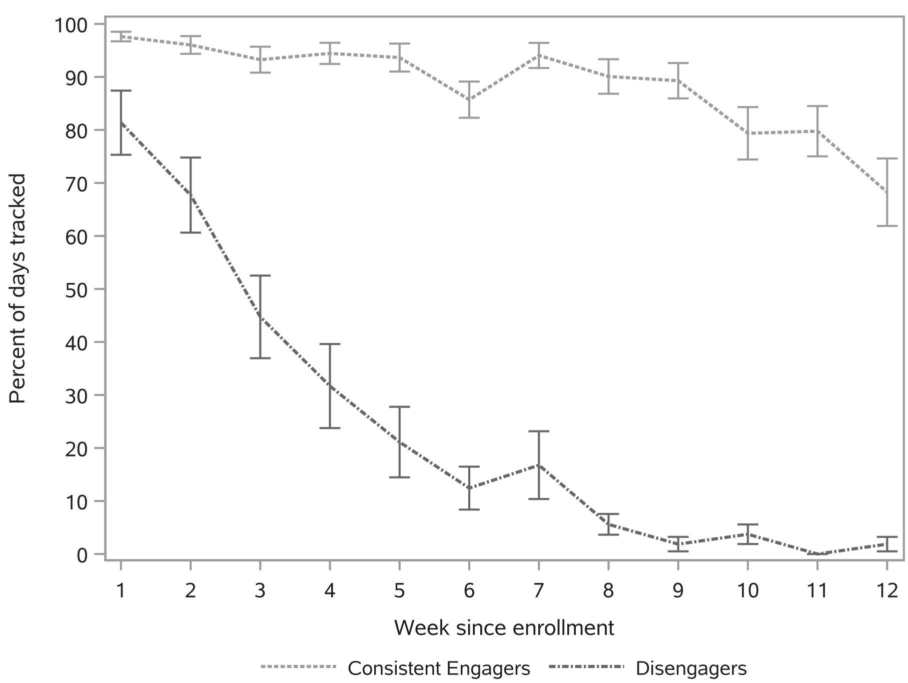

Figure 2. Empirical summary plots of weekly engagement with dietary tracking using a smartphone application over 3 months by engagement subgroup (mean±1 SE).

SE, standard error.

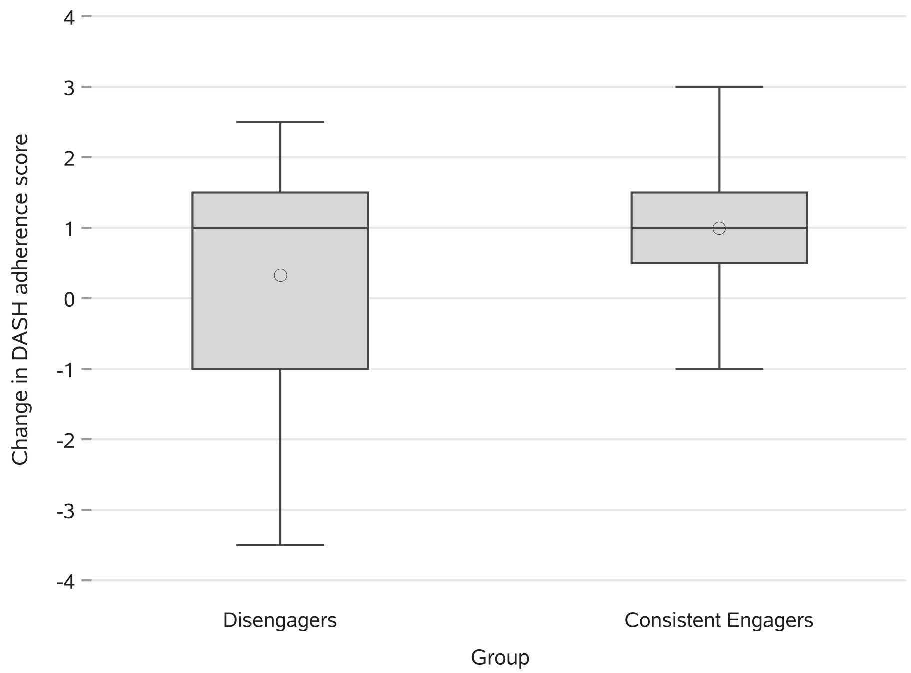

Figure 3. Box plot of empirical mean change in DASH adherence score between baseline and 3 months by engagement group.

DASH, Dietary Approaches to Stop Hypertension.

categorize participants by level of overall engagement.[42] Understanding the patterns of engagement is imperative, for without engagement there is limited exposure to the intervention leading to the potential of no intervention effects.[43] In addition, sustained engagement can facilitate habit formation,[44] another factor conducive to behavior change.[45] Although the primary outcome of this study was not to assess differences in DASH score by engagement, we did see greater improvement in DASH scores in the engagers than in the disengagers, although not statistically significant.[9] This shows the importance of future, fully powered studies to assess how patterns of engagement are associated with dietary outcomes.

An interesting finding was the lack of difference in engagement between the intervention and control groups. Although the study design does not allow for further inspection as to why the intervention group, who received tailored feedback on the basis of dietary self-monitoring, did not engage more consistently than the control group, who did not receive any feedback, we can speculate on the basis of responses to the satisfaction survey, reported elsewhere.[9] Only 55% of intervention participants felt that the feedback was helpful, and less than half felt that the DASH score reflected their actual dietary pattern.[9] This, compounded by technical issues often found in digital interventions,[46] could have impacted intervention engagement, particularly for those who felt that their dietary behaviors were not concordant with the feedback they were receiving. There are other forms of engagement, such as cognitive and emotional engagement, which were not measured in the feasibility trial that could also account for the lack of differences observed between the intervention and control groups.[47,48]

Uncovering who is more likely to disengage can help to design interventions aimed at supporting those who need it the most. In our study, we found that participants who were older, had more education, and were married or living with a partner were more likely to be consistent engagers. Previous studies have shown inconsistent results regarding engagement on the basis of sociodemographic factors.[24,49–51] Some report that younger age is associated with sustained engagement, and others report older age.[52,53] Although young people may be more willing and able to use mobile devices,[54] many studies show that if older adults have access to a mobile device and are comfortable with how to use it, then they are more likely to stay engaged.[52] In our study, older participants may have been more motivated to control their hypertension because of the increased likelihood of experiencing negative age and hypertension-related health effects. Given that interventions targeting cardiovascular disease generally focus on older adults, it is important to consider patient population characteristics during intervention design to ensure that technologies incorporate a user-friendly interface that is optimized for older adults. In addition to age, in our study, women with higher levels of education were more likely to consistently engage with dietary tracking. Others have identified education as a significant predictor of engagement.[19,50] In our study, this may reflect skills and confidence with using Nutritionix and social norms related to the perceived value of dietary tracking.[25] Although it is important to uncover variations in engagement by sociodemographic characteristics, what these differences highlight is the importance of assessing the needs and skills of the target population to ensure a high-quality digital intervention that is accessible to all.[55] Ensuring that apps are usable, meaning that they are not too difficult to understand and use effectively, for various levels of health and digital literacy is imperative. Incorporating demonstrations could improve uptake and continued engagement among a variety of populations.[56]

We also found that women who were married or living with a partner were more likely to engage. We can hypothesize that this may be due to the presence of social support. Others have also identified marital status as a significant predictor of engagement.[52] Social support, such as from a spouse or partner, has been shown to foster healthy eating habits and can provide positive encouragement, accountability, and support for overcoming the challenges associated with monitoring one's behavior.[51,57,58] Research shows that family members, such as partners, are an important source of support when using technology.[59] In fact, older adults with partners who are comfortable using technology are more likely to engage with it themselves.[60,61] Although research shows that social support is important for engagement with digital technologies, the specific mechanisms for how social support positively impacts engagement in older adults warrants further investigation.

Although our study is not unique in identifying a pattern of engagement that wanes,[62] it does point to the importance of early and often assessment of engagement as a way to support those who may become uninterested or feel that the content is not beneficial to them. Our results highlight the importance of not only tailoring interventions and the design of technologies to a population's unique needs but also accounting for the variation in engagement that occurs over time. For example, some users may perceive the app as challenging to use and thus disengage. Others may have low engagement in dietary tracking because of low motivation for behavior change.[63,64] However, given that baseline engagement was high, the steady decline in engagement across the study is likely because of decreasing motivation for dietary tracking rather than a low level of motivation at the study start, as other studies have demonstrated.[65] Identifying disengagers early and providing active communication and tailored support to distinguish between challenges may increase engagement and thus intervention exposure. This allows for allocation of additional resources to only certain participants. For people who are highly engaged, minimum support can be provided to save resources because they will be more likely to stay engaged over time. Thus, different retention approaches may be needed for certain populations to maintain engagement with digital health tools in support of behavior change.[20]

Limitations

A limitation of our study is the fact that we did not measure participants' personality traits, such as self-efficacy and motivation for dietary change, because these could be important confounding variables.[66] Motivation has been found to be associated with engagement across many studies as has self-efficacy and previous technical experience.[67] Previous technical experience can influence engagement because users are likely to engage more if their expectations match the goal of the intervention.[68] We did not directly measure expectations, but we did capture previous technology use, which did not have an impact on engagement patterns. A limitation of dietary studies is that the accuracy of the data collected is subject to potential recall and response biases.[32,69] Other limitations include the small sample size limiting our ability to identify additional patterns of engagement and power to show an effect. In addition, the results may not be widely generalizable because this study included a sample of women who were predominately White and educated.

CONCLUSIONS

Evidence suggests that higher levels of engagement with self-monitoring lead to better outcomes.[70,71] However, engagement with dietary tracking can be difficult. The DASH Cloud study sought to leverage a popular digital diet-tracking app to foster dietary self-monitoring and compliance with the DASH dietary pattern in support of BP management. This study aimed to assess the patterns of dietary self-monitoring and characterize those with the least engagement for better allocation of resources in future studies. We found 2 distinct engagement patterns in dietary self-monitoring among women enrolled in DASH Cloud. Age, education, and marital/partner status were predictive of engagement trajectory. Trajectory modeling may provide a robust method to examine differences in and predictors of self-monitoring engagement and assist in the development of strategies to promote consistency.

This study highlights an important yet underutilized methodologic approach for uncovering engagement patterns and builds on previous research reporting a general decline in engagement with apps over time. Understanding how certain individuals engage with digital technologies is an important step toward designing cost-effective behavior change interventions. Qualitative studies can extend this work to explore why certain individuals are more likely to disengage either immediately or slowly over the course of the intervention. Such work lays the foundation for improved design of digital technologies that engage individuals for a sustained period.

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CREDIT AUTHOR STATEMENT

Dori M. Steinberg: Conceptualization, Funding acquisition, Supervision, Writing — review and editing. Sandy Askew: Data curation, Formal analysis, Methodology, Software, Visualization, Writing — review and editing. Qing Yang: Methodology, Validation, Writing — review and editing. Hailey N. Miller: Conceptualization, Writing — original draft, Writing — review and editing. Miriam Chisholm: Writing — review and editing. Jacob Christy: Conceptualization, Writing — review and editing. Erin M. Spaulding: Writing — review and editing. Melissa C. Kay: Writing — original draft, Writing — review and editing.

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