Examining Patterns and Predictors of Diet Tracking via Mobile Technologies Among Women with Hypertension

by

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Thesis submitted in partial fulfillment of
the requirements for the degree of
Master of Science in the Duke Global Health Institute
in the Graduate School of Duke University

2019

ABSTRACT

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Abstract

Background: Hypertension is a primary risk factor for cardiovascular disease. Studies have shown that hypertension may have a more severe effect on cardiovascular disease outcomes among women. To mitigate this risk of hypertension in women, evidence supports that the DASH (Dietary Approaches to Stop Hypertension) diet as an effective treatment. Despite decades of evidence supporting the efficacy of the DASH diet to treat hypertension, compliance to DASH remains consistently low across all populations. However, given the importance of self-monitoring for producing behavior change, innovative efforts that utilize this strategy are needed to improve adoption of DASH on a population level. Methods**:** This thesis is a secondary analysis of a 3-month digital health intervention (DASH Cloud) to improve adoption of DASH among high-risk women conducted in Durham, NC at Duke University. Participants (N= 59) were allocated into the DASH Cloud arm (N= 30), or the attention control arm (N = 29). Both groups received publicly available booklets about the DASH diet and were asked to self-monitor their diet using a commercially available diet tracking app. Only the intervention arm received personalized feedback about their compliance to the DASH diet and skills training videos via text message. The goal of this study was to understand patterns and predictors of self-monitoring via the diet tracking app. Results: Overall, the median proportion of self-monitoring engagement was 76%. By treatment arm, the median proportion of engagement in the DASH Cloud arm and attention control arm was 68% and 85%, respectively. Significant predictors of self-monitoring include those who had 100% engagement during the first two weeks and first month of the study, were married, had a lower BMI, at least a college degree, insurance, a negative perception of their food environment, were somewhat comfortable with using apps and less likely to use an app to track medication adherence. Conclusion**:** This study provided evidence that self-monitoring of diet is high within the context of an intervention aimed at using digital health to promote compliance to the DASH diet among high-risk women. The strongest predictor of self-monitoring engagement was early engagement. This suggests that interventions aiming to improve rates of self-monitoring and improve uptake of DASH using diet tracking apps, should aim to improve early engagement to achieve success overall. However, given the small sample size of the study, future studies should include a larger population to describe patterns of self-monitoring and ascertain other predictors of engagement.

Dedication

This thesis is dedicated in loving memory of my brother, Abraham Christy. Even though this is another milestone in my life that you will miss, I know you are watching over me smiling and proud. With everything I do, I hope to touch the lives of others, like you did. To my wonderful parents, for their endless love, encouragement and prayers. I would never have had this opportunity, without all of the sacrifices you have made. A special thanks to my wife, Asha, for her unwavering love and support through all of the stressful moments of this journey. I couldn't have accomplished this without you.

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1. Introduction

1.1 Hypertension in Women

Hypertension, defined as blood pressure (BP) greater than 130/80 mmHg, is a leading, modifiable risk factor that contributes to cardiovascular disease, stroke and kidney failure. (Svetkey et al., 1999) (Whelton, Carey, Aronow, Casey, Collins, Himmelfarb, et al., 2017) Studies show that a 5-6 mmHg increase in diastolic blood pressure can increase the risk of stroke and ischemic heart disease by approximately 35-40% and 20-25%, respectively. (Kwan et al., 2013) Globally, the prevalence of hypertension is estimated to be 24% in adult men and 21% in adult women, with a disproportionate effect on women based on age. (Joseph et al., 2017) (Kearney et al., 2005) Hypertension affects men at a younger age, as in 2000 the prevalence between the ages 20-29 was 12.7%, however, after the age of 65, there is a greater increase in the prevalence and severity of hypertension in women. (Pimenta, 2012) (Kearney et al., 2005) The prevalence is significantly higher among Black women, when compared to Whites. (Gudmundsdottir, Høieggen, Stenehjem, Waldum, & Os, 2012) After a diagnosis of hypertension related heart failure, the 5-year mortality rate in women is approximately 69%, making hypertension one the leading causes of death among women in the U.S. (Hage et al., 2013) (Gudmundsdottir et al., 2012) However, effective interventions have shown promise to reduce blood pressure among women by 50% and evidence supports that the first line of treatment before drug therapy is lifestyle modification. (Sacks et al., 1999) (Whelton, Carey, Aronow, Casey, Collins, Dennison Himmelfarb, et al., 2017)

1.2 The Dietary Approaches to Stop Hypertension (DASH) Dietary Pattern is a Proven Lifestyle Intervention to Reduce Blood Pressure.

Although drug therapy remains as one of the primary solutions to reducing hypertension, dietary modifications have proved to be an efficacious and cost-effective alternative. (Forster, Veerman, Barendregt, & Vos, 2011) (Sacks, Svetkey, Vollmer, Appel, Bray, Harsha, Obarzanek, Conlin, Miller, Simons-Morton, et al., 2001) One of the most evidence-based lifestyle approaches to reducing blood pressure is the Dietary Approaches to Stop Hypertension (DASH). (Bazzano, Green, Harrison, & Reynolds, 2013) The DASH diet emphasizes fruits, vegetables, whole grains, lean meats, low-fat dairy, and limited saturated fat and sugar. (Sacks, Svetkey, Vollmer, Appel, Bray, Harsha, Obarzanek, Conlin, Miller, & Simons-Morton, 2001) Across numerous trials, DASH has shown promise to be an effective method in reducing blood pressure in those who are pre-hypertensive or hypertensive, and can lower lipid levels, suggesting that it can be used for reducing the risk of heart disease. (Appel et al., 1997) (Obarzanek et al., 2001) (Sacks, Svetkey, Vollmer, Appel, Bray, Harsha, Obarzanek, Conlin, Miller, Simons-Morton, et al., 2001) (Al-Solaiman et al., 2010) (Lopes Heno F. et al., 2003) However, this dietary modification has shown to have the greatest effect in those with hypertension, as it can reduce the systolic and diastolic blood pressure by −10.7 and −4.7 mmHg, respectively. (D. Steinberg, Bennett, & Svetkey, 2017) (Svetkey et al., 1999) Although the DASH diet has proven efficacious, non-compliance is common – recent data indicates that 0% of the population is fully compliant to DASH. (Mellen, Walsh, & Herrington, 2008) (Kwan et al., 2013) (Khan et al., 2014) (Folsom, Parker, & Harnack, 2007) To have a population impact on reducing heart disease risk as a result of elevated blood pressure, innovative solutions are necessary to improve compliance to DASH. Among the studies that have measured DASH compliance, many of them have been feeding or efficacy trials and highly-controlled studies, and very few have assessed compliance in real-life settings, where individuals make their own food choices. (Kwan et al., 2013) Similarly, limited studies have used a digital health, behavioral intervention approach. ("Effects of Comprehensive Lifestyle Modification on Blood Pressure Control," 2003) (Epstein et al., 2012) However, digital health has great potential for improving uptake of the DASH diet on a population health level.

1.3 Digital Health is a Promising Channel to Deliver DASH Interventions

In the last decade, as mobile phones have become increasingly ubiquitous, the digital divide has lessened. Currently, 95% of Americans own a mobile phone and 77% own a smartphone. (NW, Washington, & Inquiries, n.d.) Although disparities still exist among smartphone users, based on age, education attainment and income, the gap is narrowing. (Fjeldsoe, Marshall, & Miller, 2009) As such, with the proliferation of mobile technology ownership and use, digital health, or mobile health (mHealth) has become an emerging field of research that shows potential to raise health awareness, and for the prevention and treatment of chronic diseases. (Bhardwaj, Wodajo, Gochipathala, Paul, & Coustasse, 2017) Leveraging mobile phones has allowed healthcare and health information to be accessed, instantaneously, and by a broader population. (Ramirez et al., 2016) (Fjeldsoe et al., 2009) (Morton et al., 2017) This includes marginalized populations, which historically have had the poorest access to health clinics, health information and the greatest health disparities. (Ramirez et al., 2016) (Mackert, Love, & Whitten, 2009) Given the broad reach, ubiquity and portability of mobile devices, it is an attractive medium, with the greatest potential for improving population health and facilitating the uptake of the DASH diet using digital health.

1.4 Advantages of Digital Health for Delivering Behavioral Interventions

Although relatively nascent, the emergence of digital health confers many unique benefits, compared to the traditional, behavioral intervention landscape.(Mackert et al., 2009) To begin, since mobile technology has become more affordable, evidence suggests that it is being adopted more readily and used more frequently, especially among medically vulnerable populations. (NW et al., n.d.) (Rice & Pearce, 2015) (Fjeldsoe et al., 2009) Similarly, people are using it to access health information and health apps. (NW et al., n.d.) As such, studies show that through this modality, patients can manage chronic health conditions, and self-monitor health behaviors such as medication adherence, physical activity and diet. (Morton et al., 2017) (Shaw &

Bosworth, 2012) Once user data is recorded, through this platform they can receive feedback, which can reinforce their adherence to self-monitoring a particular behavior and increase the likelihood of sustaining it. (E. B. Tate et al., 2013) (Morton et al., 2017) Numerous studies have highlighted that self-monitoring is a critical component of behavioral interventions, and a rudimentary component of behavior change, but evidence suggests that it can be difficult. (Burke et al., 2012) (Bennett et al., 2018) (D. M. Steinberg et al., 2013) (Michele L. Patel, Hopkins, Brooks, & Bennett, 2019) Given that text messaging is the most commonly used feature of smartphones, it is a cost-effective strategy that can be used to provide tailored feedback and has the potential to mitigate nonadherence to self-monitoring, and facilitate behavior change. (Bauer, de Niet, Timman, & Kordy, 2010) (Bennett et al., 2018) The efficacy of tailored feedback and via text messaging has shown promise across multiple studies. (D. M. Steinberg et al., 2013) (Bennett et al., 2018) The value of text messaging feedback is further corroborated because it is a feature that can be utilized by those without smartphones. (Aguilera & Muñoz, 2011) This method of communication is timely and can be sent frequently, with low cost and high personalization. (Aguilera & Muñoz, 2011) Studies have demonstrated its effectiveness for behavior change across various health domains and further reinforces why it should be utilized in dietary interventions. (Park, Kim, & Kim, 2009) (Free et al., 2009) (Faridi et al., 2008) (Spark, Fjeldsoe, Eakin, & Reeves, 2015)

1.5 Disadvantages of Digital Health

Despite how much technology has reinvented health management practices and how behavioral interventions are delivered, challenges still exist. Currently, there are numerous commercial health apps and devices, which are used to monitor physical activity and diet, but many are not evidence-based, limiting their utility in health care and public health. (Pagoto & Bennett, 2013) (Krebs & Duncan, 2015) These apps have a propensity towards being aesthetically desirable apps, which yields high initial downloads, but waning engagement because they lack evidence and users question the apps' validity and reliability. (Pagoto & Bennett, 2013) (E. B. Tate et al., 2013) Similarly, providers lack any confidence in prescribing these digital health technologies, since they question the quality and validity of the content of the information. (Chen, Cade, & Allman-Farinelli, 2015) (Pandey, Hasan, Dubey, & Sarangi, 2013) Among those which are empirically validated, they are less likely to be used within a large population because of the rapid development of hardware and software. (E. B. Tate et al., 2013) Furthermore, the evidence related to impact of these apps on improving adherence to self-monitoring is lagging. (Pagoto & Bennett, 2013) Another key drawback of digital health is that it isolates users who are less proficient with technology, which includes primarily an older population. (Berkowsky, Sharit, & Czaja, 2017) Compounded by low proficiency, self-monitoring using technology can become even more burdensome for this group of users. More importantly, they are often excluded in designing and developing the app. (Isaković, Sedlar, Volk, & Bešter, 2016) Indeed, there is a growing demand for digital health and an oversaturation of health apps, but few, if any, are evidence-based, end-user tested and provide real-time feedback. As a result, among those who use them, attrition rates are high. However, behavioral scientists can mitigate this by maximizing the potential of technology used for behavior change.

1.6 Participant Engagement

The efficacy of behavioral interventions is highly dependent on participant engagement. Engagement is a dynamic process, which is triggered by an individual's interest, or an external recommendation that elicits a behavior change, which is sustained or discontinued. (Yardley et al., 2016) When engagement with a digital health intervention is sustained, it can facilitate a habit that is conducive to behavior change. Through observation of their behavior and by learning new skills, these users will become better equipped to identify their weakness and change their behavior. In addition, consistent feedback, or an engaging platform is pivotal for behavior change, so that users are challenged, or don't lose interest. (Taki et al., 2017) Studies suggest that initial engagement is typically high in behavioral interventions, but wanes when users become uninterested, or feel that the content isn't beneficial to them. (Leslie, Marshall, Owen, & Bauman, 2005) This is particularly important in the long-term management of chronic diseases when lapses in engagement can be deleterious, as it can reinitiate negative health behaviors and thus reduce ones self-efficacy in behavior change.

(Desroches et al., 2013) (Baumeister & Heatherton, 1996) As such, the effects of user engagement and adherence to treatment have been established across numerous studies. (Burke, Conroy, et al., 2011) (Baker & Kirschenbaum, 1998) (Wang et al., 2012) These studies have shown that those with greater consistent, engagement are more successful with behavior change and have better outcomes, compared to those with low engagement.

1.7 Behavior Change Theory

Evidence suggests that self-monitoring is important for facilitating behavior changes, and is reinforced by primarily two theoretical frameworks, which are The Social Cognitive Theory (SCT) and Self-Regulation Theory (SRT). (Payne, Turk, Kalarchian, & Pellegrini, 2018) (Boutelle & Kirschenbaum, 1998) The Social Cognitive Theory is based on the dynamic, reciprocal interaction of an individual, their behavior and environment. (Elder, Ayala, & Harris, 1999) An important construct of the Social Cognitive Theory that directs behavior change is, self-efficacy. Self-efficacy is the idea, or belief, that one has the ability and skills to accomplish a behavior across a variety of circumstances. (Elder et al., 1999) Improving one's self-efficacy predicts behavior change and is mediated by the model of self-regulation. (Strecher, McEvoy DeVellis, Becker, & Rosenstock, 1986) (Kanfer & Karoly, 1972) Self-regulation states that by observing ones thought patterns and actions, it raises an individual's awareness about their behavior and directs them how to change it. (Bandura, 1991) (Anderson, Winett, & Wojcik, 2007)

Once a behavior change strategy is identified, one can motivate themselves by establishing personal goals. (Bandura, 1991) Self-directed change that is accurate and consistent over time is fundamental for any behavioral change. (Bandura, 1991)

1.8 Dietary Self-Monitoring

Until recently, health behaviors were primarily monitored using paper-based methods. (Hutchesson, Rollo, Callister, & Collins, 2015) These methods of monitoring are not optimal as compared to digital methods since they are labor intensive, burdensome and feedback is untimely. (Wharton, Johnston, Cunningham, & Sterner, 2014) (Hutchesson et al., 2015) To mitigate this burden, research demonstrates that smartphone apps and text messaging approaches for delivering interventions can provide immediate feedback, which can help improve an individual's self-efficacy and facilitate diet changes through self-regulation. (Burke, Conroy, et al., 2011) Moreover, it has been demonstrated that frequency and consistency of documentation are the most critical aspect of dietary self-monitoring. (Peterson et al., 2014) Consistency is improved if the technologies used for documentation is perceived as easy and relevant. (Davis, 1985) In addition to immediate feedback, easier entry of foods through advanced features such as a bar code scanner, dictation or a recipe builder, can reduce user burden and improve rates of mobile self-monitoring of diet. (Tang, Abraham, Stamp, & Greaves, 2015) (Krebs & Duncan, 2015) With these features, end-users can quickly enter diet data and feel confident about using the platform. This type of dietary intervention is cost-effective and scalable, with a potential to revolutionize the way traditional in-person dietary counseling is delivered. Using technology as a platform, dietary counselors can monitor patient behavior, provide care to a greater population, and tailored, feedback can be given immediately. (Ashman, Collins, Brown, Rae, & Rollo, 2016) Some have implemented these programs, but very few studies have explored the efficacy of these strategies to improve diet quality – even fewer have focused on increasing DASH compliance in women. (Mann, Quintiliani, Reddy, Kitos, & Weng, 2014) (Acharya, Elci, Sereika, Styn, & Burke, 2011)

1.9 Rationale and Aims

The benefits of the DASH diet have been well established in reducing morbidity and mortality. In this context, non-compliance can be detrimental or undermine health improvements from the diet. By identifying and proposing strategies to increase diet tracking and increase DASH compliance, we aim to mitigate the burden of hypertension in women. Based on the current evidence, it is unclear what strategies will be the most effective to increase compliance. DASH Cloud is a study that leveraged diet data collected on a smartphone diet tracking app and evaluated the efficacy of tailored text messages, combined with a commercial diet tracking app. The primary aim of the study was to help women at risk for hypertension be more aware of their diet and make changes that are accordant with the DASH diet. In this secondary analysis, we will identify patterns and predictors of engagement with self-monitoring diet, using a commercial diet tracking app, within and across study arms. Engagement was operationalized based on the number of days where diet was tracked in the app. A valid day of tracking was defined as those who had a calorie intake of ≥ 600.

This study is novel for multiple reasons. First, there are limited studies, if any, that explore socio-demographic or personality predictors of diet tracking adherence among women. (Kwan et al., 2013) Second, by utilizing digital health as an intervention strategy, we have access to daily data on engagement and, as such, can evaluate various patterns of engagement and characteristics that might predict these patterns. Using these results, future studies can design and implement more robust and efficacious strategies that can mitigate barriers and decrease hypertension among women. In addition, the results will not be limited to the context of this study. By understanding patterns of self-monitoring and identifying characteristics of those who are adherent or nonadherent, it can be translated into the context of other behavioral studies.

2. Methods

2.1 Study Overview

The DASH Cloud study was conducted between August 2017 and March 2018 and was designed to test the feasibility and efficacy of a digital health intervention to improve diet quality. This 3-month, randomized controlled trial tested whether diet tracking using a commercially available diet track smartphone app, plus feedback on compliance to the DASH diet via text message, compared to diet tracking alone was effective for improving compliance to the DASH diet, and overall diet quality among women with hypertension. After eligibility screening and consenting to participate in the study participants (N=59) were randomized to DASH Cloud (n=30) or attention control (n=29). The Principal Investigator of the study was Dr. Dori Steinberg, Associate Professor of Nursing and Global Health. All of the procedures used in this study were approved by Duke University Institutional Review Board (protocol#: 00081972).

2.2 Setting

The study took place in Durham, NC and participants were recruited from the surrounding areas. Study assessment visits occurred at Sarah W. Stedman Center for Nutrition and Metabolism at Duke University.

2.3 Participants

The study screened women between the ages of 21-70 years old, with a body mass index (BMI) >18.5 kg/m^2. Women were included based on a self-reported diagnosis of hypertension, use of medication for blood pressure, a recent systolic measurement of 120-159 mmHg and/or a diastolic blood pressure of 80-99 mmHg. They were also required to have a smartphone with the latest operating system, a data plan and willing to receive daily or weekly texts. Having an email and fluency in written and spoken English was also required. Participants were recruited using a multi-pronged approach: 1) Flyers were distributed to gyms, community centers, grocery stores and health and wellness clinics throughout Raleigh, Durham and Chapel Hill, NC; 2) Study details were posted on research match, a national clinical trials registry, which matches participants to studies they are interested in and qualify for; 3) Posts were made on social media sites such as Twitter, Facebook and Nextdoor; and 4) We contacted participants who were ineligible for other studies, but showed interested in similar behavioral studies. Participants were excluded based on any prior cardiovascular event in the last 6 months, current cancer or psychiatric diagnosis or institutionalization, pregnancy or lactation; and enrollment in another trial similar to DASH Cloud.

2.4 Procedures

Participants who were interested in the study were directed to either website, dashcloud.org or dashcloudstudy.com. These websites directed them to complete an eligibility questionnaire on REDCap, a database used for data collection. If participants met the inclusion criteria, they were redirected to an online consent form on REDCap, which included both a brief video and text that described the study. Once they reviewed the form and watched the video, they were asked to indicate if they understood the study and had any further questions. If there were still some existing questions, they were not required to sign the online consent form and a study staff member was notified to follow-up with them. If the participant did not have any further questions, they were prompted to provide an electronic signature and date the online consent form. After this form was completed, they received an automated email, which included a secure pdf version of the consent form. The study kept this form on file for possible inspection by regulatory authorities.

After participants consented to enroll in the study, they were asked to complete a number of surveys prior to their baseline visit. Those who were unable to complete them at home, were asked to finish them at the baseline visit. These questionnaires asked them about their socio-demographics, psychosocial and behavioral characteristics. Once participants completed all of their baseline surveys, including two ASA-24 dietary recalls (Automated Self-Administered 24-Hour Dietary Assessment Tool), they were contacted by research staff to come in for a baseline study visit. During this visit, participants had anthropometric measurements taken, including their height, weight and blood pressure. During this visit, they were assessed for depression using the PHQ-8 and their health literacy was evaluated using the Vital Sign questionnaire. Before this visit, participants were asked to download the commercial diet tracking app "Nutritionix." If they hadn't already done so, they were assisted in downloading the

Nutritionix app at the first baseline visit. Once the app was downloaded, participants were instructed on how to use the app and given an opportunity to ask questions. After the baseline visit, they were asked to track their diet for a week. Upon successful completion of tracking for a minimum of 4 consecutive days, participants were invited to come back for a second baseline visit. During the second baseline visit, participants were randomized and their group assignment was revealed to them. Participants had a third follow-up visit after 3 months. Participants were compensated $25 during their second baseline visit and 3-month visit.

2.4.1 DASH Cloud

In the DASH Cloud arm, participants were asked to self-monitor their daily dietary intake and enter each item consumed, excluding water, into the commercial dietary app, Nutritionix. Dietary data was automatically uploaded from the Nutritionix app daily via an Application Programing Interface (API), which is a software that allows for the Nutritionix server to connect to the DASH Cloud intervention delivery system called Prompt. Using a secure system, Prompt stored each participant's ID, Nutritionix login credentials, phone number and all dietary information.

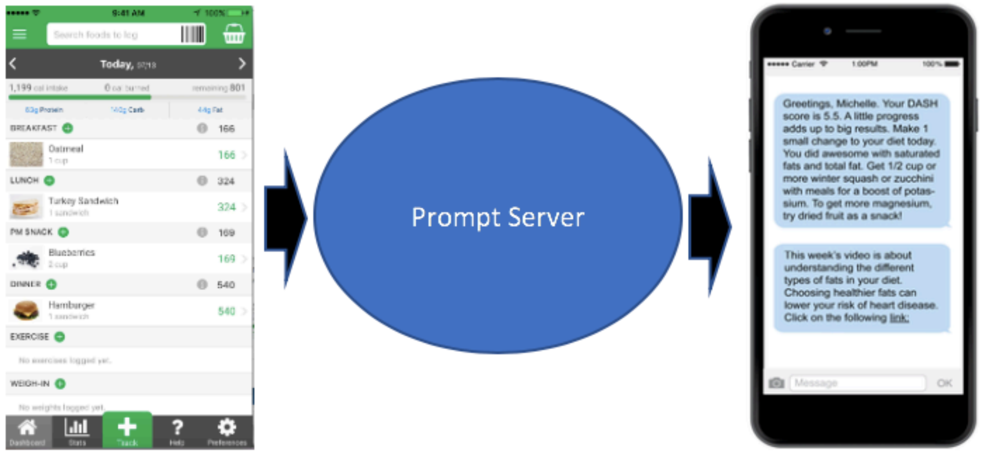

Figure 1: Data Flow From Nutritionix to Our Secure Server and The Feedback Provided to Each User in The DASH Cloud Arm

Using an algorithm, this intervention platform sent daily feedback for the first two weeks and weekly feedback for the remainder of the study. (See Figure 1) The feedback included a DASH diet score that reflected each participant's compliance to the diet. This score used a 9-point scale was based on their nutrient intake for the previous day, or week, using a validated scoring system. This included components of the DASH diet, such as potassium, sodium, magnesium, calcium, saturated fat, total fat, total protein, cholesterol, and fiber. Prompt calculated the DASH score by giving each of the above nutrients a score ranging from 0-1; 0 for low compliance, 0.5 for partial compliance, or 1 for meeting the guideline. The score total was between 0-9. (Mellen et al., 2008) In addition, these messages included a link to animated educational videos that were created by our study staff. These videos included topics related to the DASH diet (e.g., Understanding the importance of magnesium and calcium, and how to eat DASH on a budget). These text messages were intended to be motivational, provide social support and offer behavioral tips to reinforce dietary change. It also provided accountability by nudging users who were not tracking to increase their engagement by tracking their behaviors using the app. The three main elements of the intervention including self-monitoring, feedback, and skills training were designed to improve self-efficacy for dietary change and adoption of DASH.

2.4.2 Attention Control

Similar to those in the intervention, participants in the attention control arm were asked to input their daily diet into the Nutritionix app and their dietary data was retrieved by our servers. However, compared to the intervention group, they only received a publicly available booklet that contained information about the DASH diet and did not receive any tailored feedback or skills training videos via text. The attention control arm was asked to self-monitor their diet too, so that we could isolate the effect of the feedback and skills training delivered via text message.

2.5 Patterns of Engagement

To describe patterns of engagement we used self-monitoring data collected by the diet tracking app, Nutritionix. Only data from those who were randomized were used. We assessed engagement by first assessing the number of valid days tracked within the 12-week study. A valid day of tracking was defined as a day with calories ≥600, as evidence suggests that a calorie intake below 600 is less likely to be plausible.

(Subar et al., 2001) Days without a calorie count were considered missing and those that were < 600 calories were considered invalid. Engagement data was collected each week until the participant completed the study. To describe patterns of self-monitoring among the participants, engagement with diet tracking was analyzed using the following categories.

2.5.1 Overall Engagement

The overall proportion of valid days tracked over 84 days was assessed. Based on prior studies, high overall engagement was then categorized into those who self-monitored ≥ 80 and 100%. (Bennett et al., 2018) (Vincze, Barner, & Lopez, 2004)

2.5.2 Weekly Engagement

The number of days of tracking was organized by week and the proportion of weekly self-monitoring was categorized into low, medium and high. Low weekly engagement was defined as 0-2 days, medium engagement 3-4 days and high engagement was 5-7 days. (Boutelle & Kirschenbaum, 1998) (O'Neil, 2001) The weekly total proportion of participants are reported by group and overall.

2.5.3 Monthly Engagement

Similarly, monthly engagement was assessed using the proportion of days tracked per month. The proportion was calculated by enumerating the total number of valid days recorded out of 28 days. Furthermore, compliance to dietary self-monitoring was categorized into 3 levels: low, medium and high. Low was defined as 0-10 days in a month, medium 11-20 days in a month, and high >20 days in a month.

2.5.4 Early Engagement

To assess the effect of early adherence to dietary self-monitoring, the proportion of those who recorded their diet every day for the first two weeks and the first month were calculated.

2.6 Clinical and Socio-Demographic Predictors

To understand the characteristics of those who self-monitor their diet, we assessed the association between engagement and several baseline socio-demographic and clinical characteristics. The proportion of those within each category were reported, in addition to the p-value. The characteristics measured are described below.

2.6.1 Anthropometrics

Body weight and height were collected by study staff at the first baseline visit. During this visit height was measured twice and recorded to the nearest 0.1 cm with a Portrod Wall Mounted height rod. Weight was measured twice and recorded to the nearest 0.1 kg using a Scale-Tronix 5005 scale. The baseline height and weight, and body mass index kg/m^2 (BMI) were calculated for each participant and categorized into one of the following BMI classes: underweight, normal weight, overweight, obesity, class 1 obesity, class 2 obesity and class 3 obesity. To compare different levels of BMI and given the distribution of our data, we dichotomized this variable into two categories comparing those who did not have obesity (N = 17) vs. those who had obesity (N= 42).

2.6.2 Blood Pressure

Blood pressure was collected at the in-person assessment visits. Prior to measurement, participants were asked if tobacco or coffee was consumed 30 minutes before the visit. If participants met this criteria, they were asked to sit quietly for 5 minutes before their blood pressure was measured. Otherwise, it was only measured after 30 minutes. After participants rested for 5 minutes, their blood pressure was measured 3 times with 30-second intervals in-between each measurement, using an Omron HEM-907XL. All 3 measurements were recorded, but the average was used for analysis. Using the average blood pressure, participants were categorized based on their severity of hypertension using the new blood pressure guidelines. Using the new guidelines for managing blood pressure, a binary variable was created that compared those with healthy blood pressure levels (N = 18), which is defined as a blood pressure <120/80 mmHg compared to those who had a measurement ≥ 120/80 mmHg (N = 41). (Whelton, Carey, Aronow, Casey, Collins, Dennison Himmelfarb, et al., 2017)

2.6.3 Socio-demographics

Socio-demographics were collected at baseline using a general survey and included age, race/ethnicity, educational attainment, marital status, employment, insurance status and the number of children within the household. Age was continuous and the following variables were collapsed and dichotomized: White vs. non-White college degree or above vs. less than college degree, married/living with partner vs. not married/living alone, employed vs. unemployed, insured vs. uninsured and children in the household vs. no children in the household.

2.7 Behavioral Predictors

To understand the characteristics of those who self-monitor their diet, we assessed the association between engagement and several behavioral characteristics. The proportion of those within each category were reported, in addition to the p-value. The constructs measured are described below.

2.7.1 Sleep

Duration of sleep was measured using the Behavioral Risk Factor Surveillance System (BRFSS) item assessing sleep. Participants were asked, *On average how many hours of sleep do you get per night?* (Jungquist et al., 2016) The variable was dichotomized into those who received insufficient sleep, which is defined as < 7 hours and those who had sufficient sleep ≥ 7 hours. (D. Steinberg, Christy, et al., 2017)

2.7.2 Medication Nonadherence

Medication nonadherence was assessed at baseline and at 3-months using the *Patient Preference and Adherence scale.* This is a 24-item measure that measured the extent of nonadherence and the reasons for nonadherence during the past 7 days. A 3-item scale measured the extent of nonadherence on a 5-point Likert scale and asked how often participants missed doses of their antihypertensive medications. The variable was dichotomized into adherent and non-adherent. Non-adherence was defined as a response other than 'never' on any extent item. Additionally, a 21-item scale assessed the reasons that may have interfered with adherence, which included reasons such as, *I forgot, I was busy, they cost a lot of money.* The frequency of each reason for non-adherence was reported. (Voils et al., 2014)

2.7.3 Physical Activity

Participant physical activity was measured using the *Global Physical Activity Questionnaire (GPAQ)*, which is internationally validated and developed by the World Health Organization (WHO). This 16-item scale measures an individual's physical activity in 3 domains (work, transport and leisure time) and time spent in sedentary behavior. (Cleland et al., 2014) Physical activity was assessed based on level of metabolic equivalents (METS), which were low, medium and high and those who met WHO recommended guidelines, compared to those who did not. High was classified as those engaged in vigorous-intensity activity for at least 3 days a week and achieved at least 1,500 METS, or 7 days or more of low, moderate or vigorous-intensity activity, achieving at least 3,000 METS per week. Moderate activity was classified as those who had 3 or more days of vigorous-intensity activity, or at least 20 minutes per day, or 5 or more days of moderate-intensity activity or walking for at least 30 minutes per day, or 5 or more days of walking, moderate, or vigorous-intensity activity for at least 600 METS per week. Low physical activity was defined as those who couldn't be categorized into moderate, or high physical activity. Those who met WHO guidelines had at least 150 minutes of moderate-intensity aerobic physical activity throughout the week, or least 75 minutes of vigorous-intensity aerobic physical activity throughout the week, or an equivalent combination of moderate and vigorous-intensity activity.

2.7.4 DASH Compliance

Dietary intake was assessed using the Automated Self-Administered (*ASA-24*) dietary recall. This self-administered, dietary tool asks participant to indicate the foods they ate the previous day. Participants were asked to complete 1 weekday and 1 weekend recall. DASH compliance was assessed using a validated dietary index that included 9 nutrient targets for sodium, potassium, magnesium, calcium, fiber, cholesterol, total fat, saturated fat, and protein (Mellen, Walsh, & Herrington, 2008) The scale has a range from 0-9, with "0" indicating poor compliance, and "9" equated to full compliance. Compliance was dichotomized as those who have a DASH score ≥ 4.5, compared to those who had a score < 4.5. (D. Steinberg, Kay, Burroughs, Svetkey, & Bennett, 2019)

2.8 Psychosocial Predictors

To understand the characteristics of those who self-monitor their diet, we assessed the association between engagement and several psychosocial characteristics. The proportion of those within each category were reported, in addition to the p-value.

The following characteristics were measured at baseline and only the PHQ-8 was assessed again at the 3-month follow-up. The constructs measured are described below.

2.8.1 Depression

Depression was assessed using the 8-item survey of the Patient Health Questionnaire (*PHQ-8)*. This is a valid measure used to diagnose depressive symptoms in general populations. (Kroenke et al., 2009) The measure asks questions pertaining to how much a participant's mood, diet and energy level is affected during the last week. Examples of these are: *Feeling down, depressed, or hopeless, Trouble falling or staying asleep, or sleeping too much* and *Poor appetite or overeating.* (Kroenke et al., 2009) The scale ranges from 0-24 and there is evidence that a score of at least 10 indicates clinically significant depression. The total score is categorized into 5 categories that indicate the severity of depression as following: 0-4 - No significant depressive symptoms, 5-9 - Mild depressive symptoms, 10-14 - Moderate, 15-19 - Moderately severe, 20-24 - Severe. Given the distribution of data in our sample we assessed depression by dichotomizing the variable into those without depression < 5 ($N = 37$), compared to those who were depressed ≥ 5 ($N = 22$).

2.8.2 Technology Use

Technology use consisted of questions that described frequency of use, types of devices used, if wearable technology was used, confidence in using apps and if any apps are used to monitor health. The frequency of cell phone and text messaging use were dichotomized into those who used them often, compared to those who were infrequent users. Existence of an unlimited SMS plan, internet service and WIFI service at home were dichotomized into yes, or no. If apps or wearables were used to monitor blood pressure, weight, physical activity, diet and medication adherence, they were dichotomized similarly. Comfort in using apps were categorized into those that were comfortable, compared to those who were somewhat comfortable. These variables were dichotomized as such, due to the non-normal distribution and given that the majority of participants answered as being very comfortable.

2.8.3 Personality

The Big Five Inventory is a 44-item assessment that is used to measure 5 domains (Extraversion, Agreeableness, Conscientiousness, Neuroticism, Openness) of an individual's personality on a 5-point Likert scale. High scores indicate the strength of the personality trait. The scores are reported using a median split for each category and they were categorized into high vs. low. This was created because the measure is typically reported as continuous, but it lacks any guidelines that indicate how it should be reported otherwise – creating a binary variable was easier to conceptualize and the most practical to use in the context of our study. (Iacobucci, Posavac, Kardes, Schneider, & Popovich, 2015) Using a 5-point scale, respondents were asked to indicate the extent to which they agree or disagree with the statement. Examples questions from each domain include: *Is talkative; Is helpful and unselfish with others; Does a thorough job; Is depressed, blue; Is original, comes up with new ideas,* respectively. (John & Srivastava, 1999)

2.8.4 Health Literacy

The *Newest Vital Sign* is a 6-item measure that assesses an individual's health literacy and numeracy, based on a nutrition label. Participants are asked to read a nutrition label from a pint of ice cream and answer questions that pertain to it. Examples include: *If you eat the entire container, how many calories will you eat?* and *If you usually eat 2,500 calories in a day, what percentage of your daily value of calories will you be eating if you eat one serving?* A score of at least 4 indicates adequate literacy. A binary variable was created, indicating adequate literacy for those who score ≥ 4 and limited literacy for those who score < 4. (Shealy & Threatt, 2016)

2.8.5 Food Environment

The *Perceived Availability of Healthy Food Questionnaire* is a 3-item measure, which assess an individual's perception of the healthy food available in their neighborhood on a 5-point Likert scale. A binary variable was created using a median split. Higher scores indicated poor perception of healthy food availability in their neighborhood. Items on the measure include: *1) A large selection of fruits and vegetables is available in my neighborhood; 2) A large selection of low-fat products is available in my neighborhood; and 3) The fruits and vegetables in my neighborhood are of a high quality.* (Gustafson et al., 2011)

2.9 Data Analysis

For descriptive analysis, normal distributed variables were summarized and reported as means and standard deviations (SD). Medians and interquartile ranges (IQR) were reported for non-normal distributions. Since engagement was not normally distributed, the median and interquartile range (IQR) are reported to assess adherence using the different categories below.

Predictors of engagement were examined using baseline demographics and the constructs measured. Since the proportion of self-monitoring had a non-normal distribution, comparisons for each predictor was measured using the Wilcoxon Rank Sum Test. We assessed the association between these predictors and reported the overall median engagement. Associations between predictors and the thresholds of 80 and 100% engagement were determined using chi-square (x^2) independence test or a Fisher's exact test. P-values were reported to indicate any statistical significance. Statistical significance was < .05 for all tests. Data analysis was done using Stata/SE 15.1. (StataCorp. 2017. *Stata Statistical Software: Release 15*. College Station, TX: StataCorp LLC).

3. Results

3.1 Baseline Characteristics

Participants in the DASH Cloud study (n = 59) had a mean age of 49.9 ± 11.9 years and 83% had a college degree or greater. The majority of the sample was White (73%), insured (97%), employed (76%) and married/living with a partner (61%). Participants had a mean BMI of 33.9 kg/m^2 ± 7.6 and 71% had obesity, defined as a BMI ≥ 30 kg/m^2. At baseline, the mean (SD) systolic blood pressure was 122.9 (14.2) mmHg and the mean (SD) diastolic blood pressure of 80.2 (8.8) mmHg. Based on the components in the DASH diet, the mean DASH score was 2.2 (1.3). The majority (69%) were classified as having an elevated blood pressure or greater, according to the new blood pressure guidelines from the American Heart Association/American College of Cardiology, which is defined as any measurement over 120/80 mmHg. (Whelton, Carey, Aronow, Casey, Collins, Himmelfarb, et al., 2017)

Table 1: Baseline Characteristics

Baseline Characteristic	**Mean (SD)**
Age (Years**)**	49.9 (11.9)
Body Mass Index (kg/m^2**)**	33.9 (7.6)
Systolic (mmHg**)**	122.9 (14.2)
Diastolic (mmHg**)**	80.2 (8.8)
DASH Score	2.2 (1.3)
	Proportion (N)
DASH Score	

Less than 4.5	88% (52)
Greater or equal to 4.5	12% (7)
Body Mass Index (BMI)	
Has Obesity (BMI ≥ 30 kg/m^2)	71% (42)
Does not have obesity (BMI <30 kg/m^2)	29% (17)
Blood Pressure (BP)	
Elevated Blood Pressure or Greater (BP ≥ 120/80)	69% (41)
Normal Blood Pressure (BP < 120/80)	31% (18)
Socio-Demographics	
Marital Status	
Married/Living with Partner	61% (36)
Not Married/Living Alone	39% (23)
Children	
Children in Household	41% (23)
No Children in House	59% (33)
Education	
College Degree or Above	83% (49)
Less than College Degree	17% (10)
Race	
White	73% (43)
Non-White	27% (16)
Insurance	
Insured	97% (57)
Uninsured	3% (2)
Employment Status	
Employed	76% (42)
Unemployed	24% (13)
Behavioral	
Sleep	
Sufficient Sleep (≥ 7 hours)	68% (40)

Insufficient Sleep (< 7 hours)	32% (19)
Blood Pressure Medication Use	
Yes	49% (29)
No	51% (30)
Blood Pressure Medication Nonadherence[1]	
Nonadherent	29% (8)
Adherent	71% (20)
WHO Physical Activity Level[2]	
Low	60% (35)
Medium	24% (14)
High	16% (9)
Meets WHO Physical Activity Recommendation	
Meets Recommendation	48% (28)
Does Not Meet Recommendation	52% (30)
Psychosocial	
Depression	
Depressed (5-24)	37% (22)
Not Depressed (0-4)	63% (37)
Health Literacy	
Adequate Health Literacy (4-6)	92% (54)
Limited Health Literacy (0-3)	8% (5)
Food Environment Perception[3]	
Negative Perception	51% (30)

[1] A 3-item scale measured the extent of nonadherence on a 5-point Likert scale and nonadherence was defined as a response other than 'never' on any extent item.
[2] High: Vigorous-intensity activity for at least 3 days a week and achieved at least 1,500 METS, or 7 days or more of low, moderate or vigorous intensity activity, achieving at least 3,000 METS per week.
Moderate: 3 or more days of vigorous-intensity activity or at least 20 minutes per day, or 5 or more days of moderate-intensity activity or walking for at least 30 minutes per day or 5 or more days of walking, moderate, or vigorous-intensity activity for at least 600 METS per week.
Low: Those who couldn't be categorized into moderate, or high physical activity.
[3] A 3-item measure, which was dichotomized using a median split. Higher scores indicated a negative perception.

Positive Perception	49% (29)

3.2 Patterns of Engagement

3.2.1 Overall Engagement

The overall median proportion of days self-monitored was 76% (IQR: 27-95) over the 12-week intervention. The median (IQR) proportion of engagement in the attention control arm was greater, although not statistically significant, compared to the intervention arm, [85% (IQR: 27-98) vs. 68% [IQR: 29-92]; p = 0.24]. Similarly, out of a possible 84 days of tracking, the overall median number of days tracked was 64 (IQR: 23-80). Although again not statistically significant, the median (IQR) number of days tracked was greater in the attention control arm, compared to the intervention arm [71 days (IQR: 23-82) vs. 57.5 days (IQR: 24-77); p = .24].

3.2.2 Engagement by Week

As is depicted in Figure 2, the median days tracked by week was comparable across groups for the first 2 weeks of the study. At 2 weeks we saw a deviation between the arms, as the attention control arm had higher engagement. However, by week 6, engagement was similar again, as both arms showed a steady decrease in engagement and both arms had a median engagement of 5 days. After week 6, the median engagement level remained comparable between the study arms, until week 8. At week 8, the median days tracked in DASH Cloud and attention control arm was 3.5 days and 7 days, respectively. Engagement improved at week 9, but the difference was stark between weeks 10 and 12, as the attention control arm had greater adherence. By the end of the study, the attention control arm had a median of 7 days, compared to 0 days in the intervention arm.

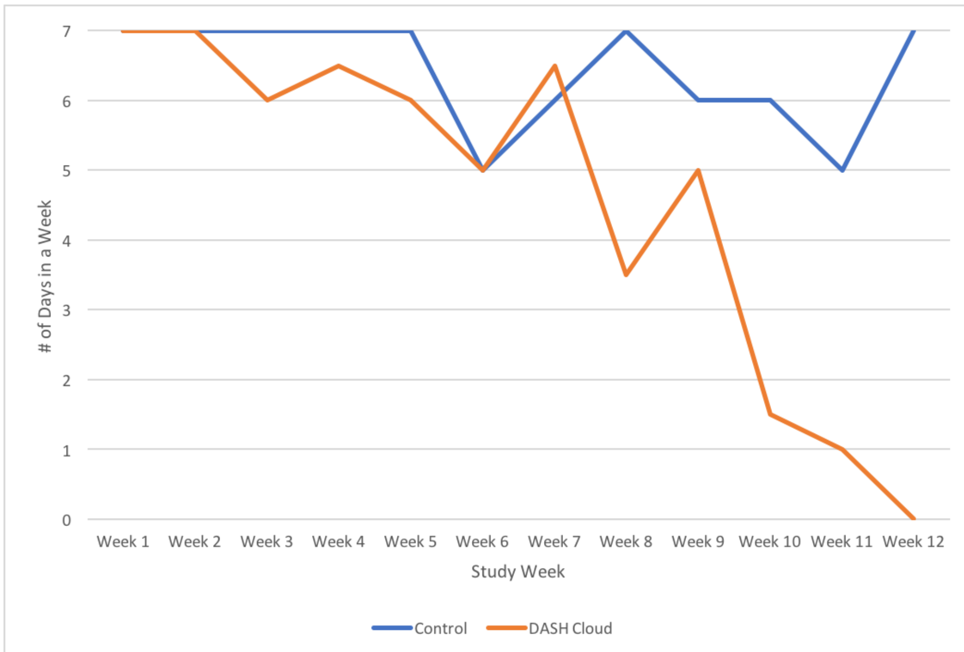

Figure 2: Weekly Median Engagement by Group

Combining both study arms together, Figure 3 below shows the proportion of engagement by category over time. The proportion of those who had high engagement gradually declined until week 6, but remained above 50% until week 10. Simultaneously, there was a relatively steady increase in the proportion of those who had low and medium engagement. However, at week 8, there was dramatic shift in these categories, as the proportion of those who had low engagement increased, while those who had medium engagement decreased. At week 10, the proportion of those who had low or medium engagement remained steady for the duration of the study, while there was an attenuation of high overall engagement across arms, as it fell below 50%.

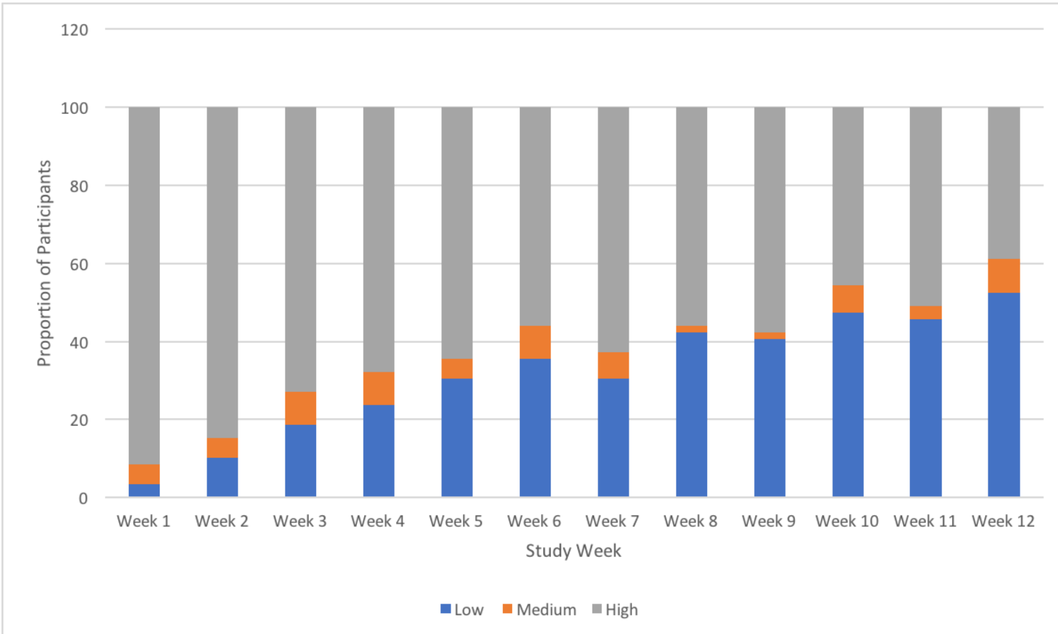

Figure 3: Proportion of Weekly Engagement Overall

Figure 4 examines differences in weekly engagement by study arm. In the intervention arm, the proportion of those who had high weekly engagement was consistently greater than the attention control arm until week 5. Adherence among the intervention arm declined, but remained consistently above 50% until week 10. At week 10 and week 12, the proportion of high engagement in the intervention arm dropped to 33.3% and 23.3%, respectively. The proportion of participants with high engagement in the attention control arm was greater than 50% for the duration of the study.

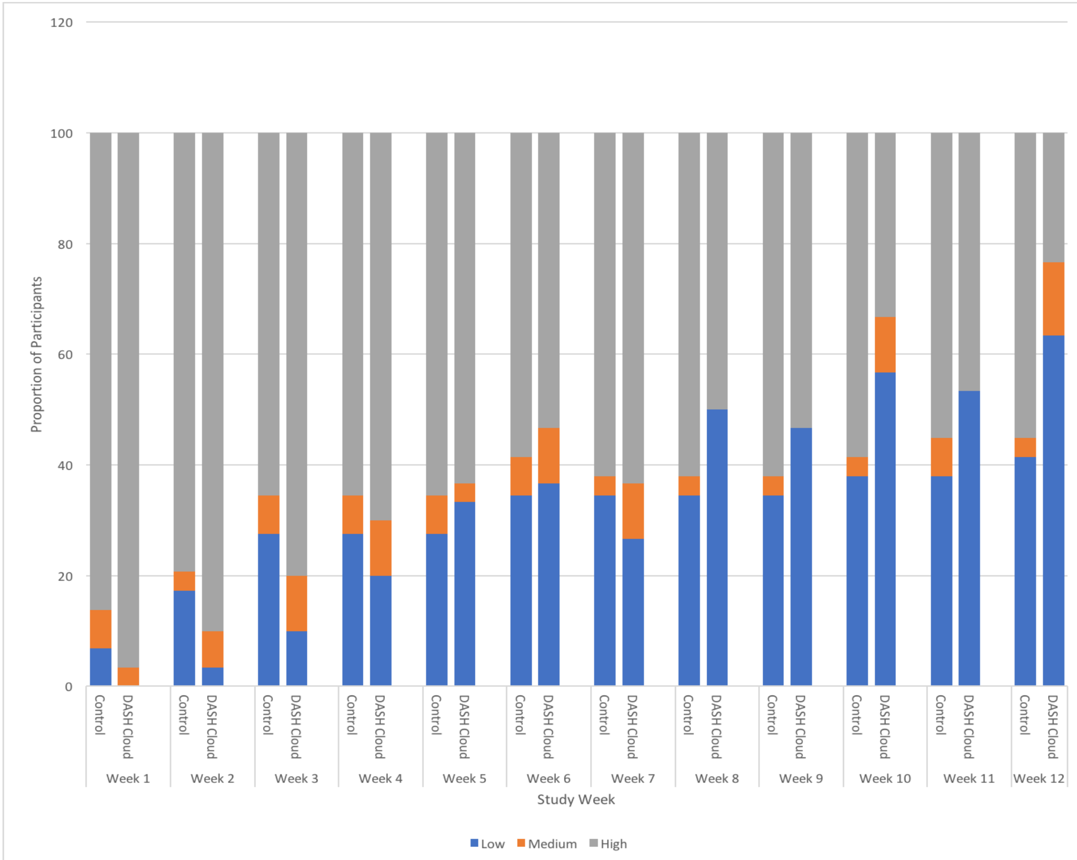

Figure 4: Weekly Proportion of Engagement By Group

3.2.3 Engagement by Month

Figures 5 and 6 highlight changes in engagement on a monthly level. The median number of days and the median proportion of engagement in the first month was consistently higher in the attention control arm, when compared to the intervention arm. However, the median proportion of days engaged in a month was at least 69% in both arms, until the end of 2nd month. In the 3rd and final month of the study, the median proportion was 78.6% and 26.8% in the attention control arm and DASH Cloud arm, respectively.

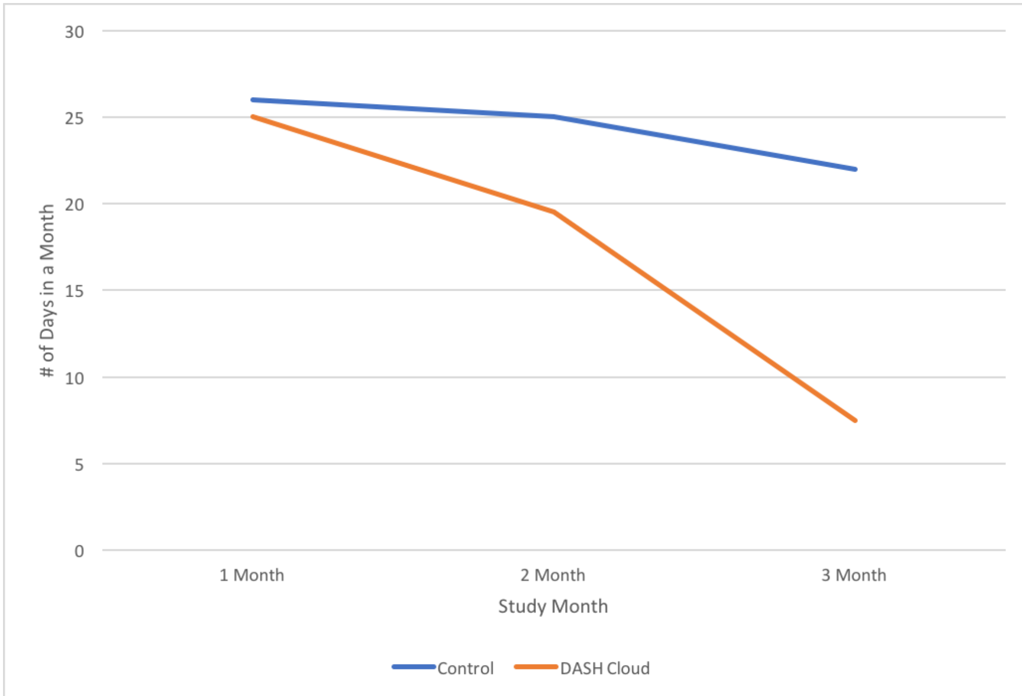

Figure 5: Monthly Median Days of Engagement

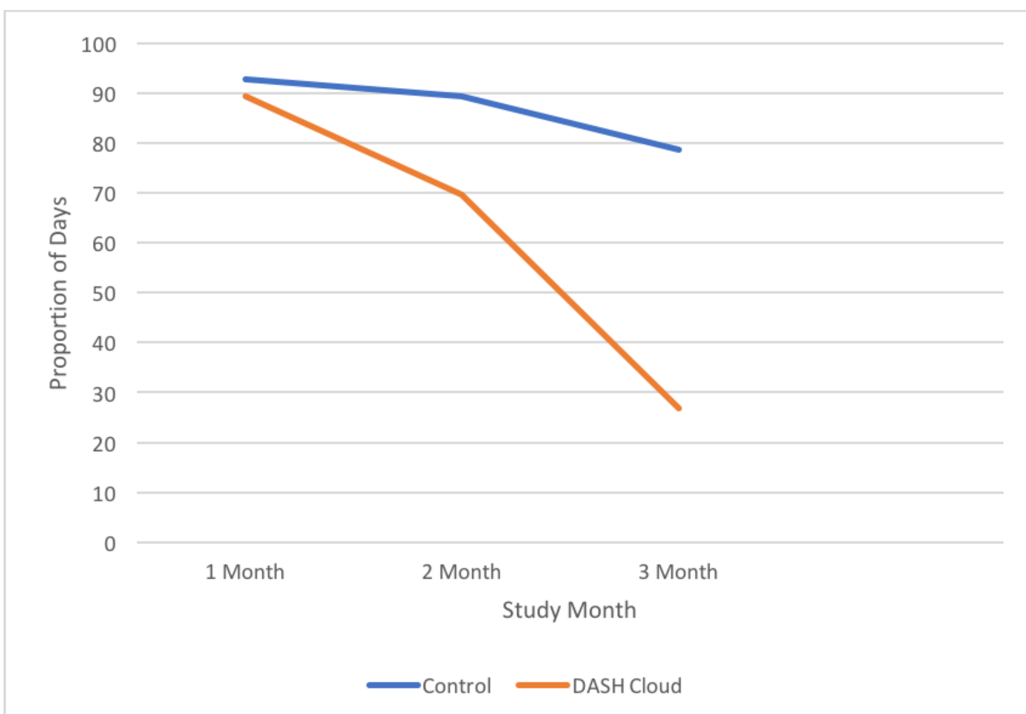

Figure 6: Monthly Median Proportion of Engagement

Similarly, Figure 7 illustrates monthly engagement by category. Both arms had at least 50% high engagement, until the 3rd month. However, at 3 months, the proportion of those who had high engagement was 51.5% in the attention control arm and 26.7% in the intervention arm.

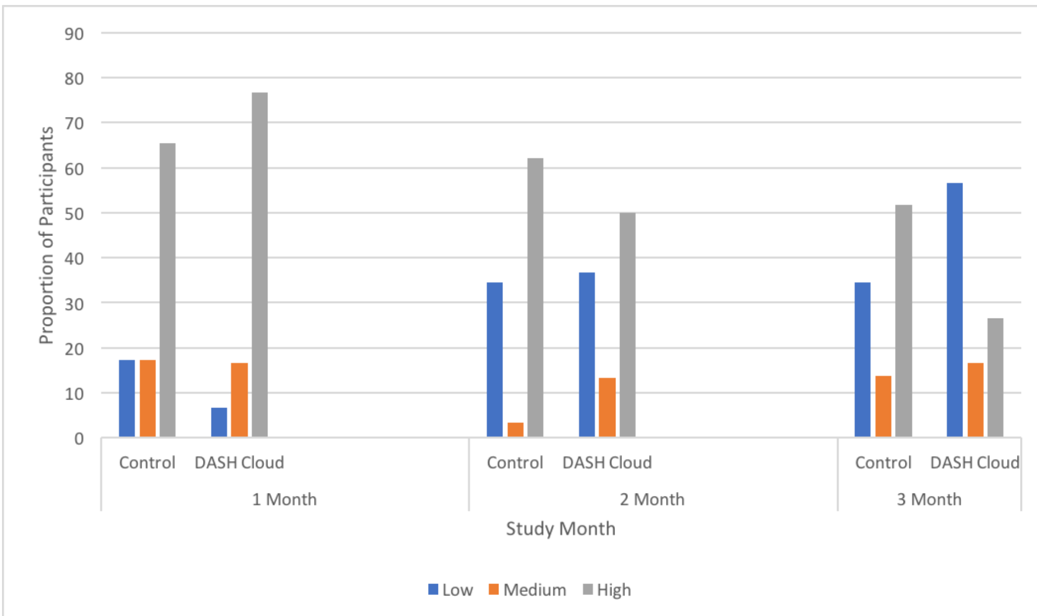

Figure 7: Monthly Proportion of Engagement

3.2.4 Early Engagement

Early engagement of self-monitoring was moderate in this study as 56% (n=33) tracked their diet daily for the first two weeks and 36% (n=21) tracked their diet daily during the first four weeks. Engagement was high even among those who failed to successfully record their diet consistently during the first two weeks and four weeks of the study. Among those that did not track their diet consistently during the first two weeks, the median engagement was 12 days [IQR: 8-13]. Similarly, at four weeks, the median engagement was 21.5 days [IQR:15-25].

3.3 Predictors of Engagement

Predictors of engagement were assessed by combining the two study arms together. As shown in Table 2, there were significant differences in the proportion of engagement based on the following socio-demographic predictors. Those who were married, or living with a partner had a significantly higher median (IQR) engagement, when compared to those who were not married, or living alone [85% (IQR: 44 98) vs. 44% (IQR: 25-92); p=.03]. Those who had at least a college degree had significantly higher median (IQR) engagement, compared to those who had less than a college degree [83% (IQR: 39-95) vs. 31% (IQR: 20-60); p=.04]. Lastly, there was significantly higher median (IQR) engagement among those who had insurance, compared to those who didn't have insurance [76% (IQR: 35-95) vs. 11% (IQR:6-17); p = .04]. There were no significant differences based on number of children in household, race and employment.

Table 2: Proportion of Engagement Based on Socio-demographics

	Overall Proportion of Engagement		80% Engagement		100% Engagement	
	Median Proportion of Engagment (IQR)	P Value	Proportion of Participants (N)	P Value	Proportion of Participants (N)	P Value
Marital Status		p = .03*		p = .04*		p = .04*
Married/Living with Partner	85% (44-98)		58% (21)		17% (6)	
Not Married/Living Alone	44% (25-92)		30% (7)		0% (0)	
Children		p = .38		p = . 30		p = 1.00
Children in Household	85% (39-96)		57% (13)		(2) 9%	
No Children in House	74% (27-94)		42% (14)		(3) 9%	
Education		p = .04*		p = .08		p = 1.00
College Degree or above	83% (39-95)		53% (26)		10% (5)	
Less than College Degree	31% (20-60)		20% (2)		10% (1)	
Race		p =.34		p= .35		p = .18
White	81% (29-95)		51% (22)		14% (6)	
Non-White	72% (26-92)		38% (6)		0% (0)	
Insurance		p = .04*		p = . 49		p = 1.00
Insured	76% (35-95)		49% (28)		11% (6)	
Uninsured	11% (6-17)		0% (0)		0% (0)	
Employment Status		p = .26		p = .18		p = .58
Employed	68% (27-93)		41% (17)		7% (3)	
Unemployed	92% (29-94)		62% (8)		15% (2)	

*<.05 using Wilcoxon Rank Sum Test, Chi-Square (x2) Independence test, or a Fisher's Exact Test

Table 3 indicates that there were significant differences in engagement based on previous technology use. Participants who had reported being somewhat comfortable using apps had significantly higher median (IQR) engagement, compared to those who rated being comfortable [92% (IQR: 85-96) vs. 49% (IQR: 24-94): p = .01] Similarly, those who had never used an app for medication adherence reported a significantly higher median (IQR) engagement, when compared to those who did use an app to track medication adherence [82% (IQR:35-95) vs. 24% (IQR:15-44); p = .03]. There were no significant differences based on how often a cellphone was used, an unlimited texting plan, current subscription to internet access at home, app use, using an app to track blood pressure, using an app to track weight, physical activity or diet, or if none of the behaviors mentioned were tracked using app. In addition, there were no significant differences based on using an electronic or wearable device to track blood pressure, weight, physical activity, diet or if none of the behaviors mentioned were tracked using an electronic or wearable.

Table 3: Proportion of Engagement By Technology Use

	Overall Proportion of Engagement		80% Engagement		100% Engagement	
	Median Proportion of Engagment (IQR)	P Value	Proportion of Participants (N)	P Value	Proportion of Participants (N)	P Value
How often do you use your cellphone?		p = 0.98		p = 1.00		p = 1.00
Often	76% (27-95)		47% (27)		11% (6)	
Less Than Often	61% (29-94)		50% (1)		0% (0)	
Do you have an unlimited texting plan?		p = 0.51		p = 0.61		p = 1.00
Yes	76% (35-95)		48% (26)		11% (6)	
No	94% (29-99)		67% (2)		0% (0)	
Do you currently subscribe to internet service at home? This does not include your cell phone data plan (3G/4G).		p = 0.36		p = 0.48		p = 1.00
Yes	76% (27-94)		47% (27)		10% (6)	
No	95% (0)		100% (1)		0% (0)	
Do you use apps?		p = 0.41		p = 1.00		p = 1.00
Yes	76% (27-95)		48% (28)		10% (6)	
No	29% (0)		0% (0)		0% (0)	
How comfortable are you using applications (apps) on your smartphone?		p = 0.01*		p = 0.003*		p = 1.00
Comfortable	49% (24-94)		37% (15)		10% (4)	
Somewhat Comfortable	92% (85-96)		81% (13)		13% (2)	
Have you ever used an app to track the following: (choice=Blood pressure)		p = 0.45		p = 0.66		p = 1.00
Yes	94% (74-98)		60% (3)		0% (0)	
No	76% (27-94)		46% (25)		11% (6)	
Have you ever used an app to track the following: (choice=Weight)		p = 0.22		p = 0.33		p = 0.23
Yes	57% (24-93)		40% (10)		4% (1)	
No	82% (29-96)		53% (18)		15% (5)	
Have you ever used an app to track the following: (choice=Physical activity)		p = 0.89		p = 0.40		p = 0.08
Yes	69% (35-98)		43% (16)		16% (6)	
No	84% (27-93)		55% (12)		0% (0)	
Have you ever used an app to track the following: (choice=Diet)		p = 0.20		p = 0.16		p = 1.00
Yes	60% (24-93)		39% (12)		10% (3)	
No	84% (32-96)		57% (16)		11% (3)	
Have you ever used an app to track the following: (choice=Medication)		p = 0.03*		p = 0.05		p = 1.00
Yes	24% (15-44)		0% (0)		0% (0)	
No	82% (35-95)		52% (28)		11% (6)	
Have you ever used an app to track the following: (choice=None of the above)		p = 0.49		p = 0.20		p = 0.33
Yes	85% (52-95)		67% (8)		0% (0)	
No	69% (27-95)		43% (20)		13% (6)	
Have you ever used an electronic or wearable device to track the following: (choice=Blood pressure)		p = 0.16		p = 0.60		p = 0.28
Yes	95% (75-100)		67% (2)		33% (1)	
No	75% (27-94)		46% (26)		9% (5)	
Have you ever used an electronic or wearable device to track the following: (choice=Weight)		p = 0.88		p = 1.00		p = 1.00
Yes	61% (24-99)		50% (1)		0% (0)	
No	76% (29-94)		47% (27)		11% (6)	
Have you ever used an electronic or wearable device to track the following: (choice=Physical activity)		p = 0.7		p = 0.96		p = 1.00
Yes	64% (24-96)		47% (17)		11% (4)	
No	76% (36-94)		48% (11)		9% (2)	
Have you ever used an electronic or wearable device to track the following: (choice=Diet)		p = 0.20		p = 0.48		p = 1.00
Yes	99% (0)		100% (1)		0% (0)	
No	76% (27-94)		47% (27)		10% (6)	
Have you ever used an electronic or wearable device to track the following: (choice=None of the above)		p = 0.53		p = 0.57		p = 1.00
Yes	81% (49-94)		52% (11)		10% (2)	
No	64% (24-95)		45% (17)		11% (4)	

*<.05 using Wilcoxon Rank Sum Test, Chi-Square (x2) Independence test, or a Fisher's Exact Test

Table 4 shows that there were significant differences based on early engagement. Participants who tracked every day during the first two weeks had significantly higher median (IQR) engagement compared to those who did not track every day during the first 2 weeks [94% (IQR: 69-99) vs. 32% (IQR: 13-76); p = <.001]. Engaging every day in the first 4 weeks was also significantly predictive of overall engagement. Those who tracked every day for the first 4 weeks had a significantly higher overall median (IQR) engagement, compared to those who tracked anything less than every day during the first 4 weeks [98% (IQR: 94-100) vs. 39% (IQR: 20-81); p <.001]. Similar results were seen for early engagement at both 2 and 4 weeks when looking at the proportion of participants who achieved an overall proportion of engagement of 80% and 100%.

Table 4: Proportion of Engagement Based on Early Engagement

	Overall Proportion of Engagement		80% Engagement		100% Engagement	
	Median Proportion of Engagement	P Value	Proportion of Participants (N)	P Value	Proportion of Participants (N)	P Value
2 Week Engagement		p <.001*		p = .001*		p = .03*
Tracked every day (33)	94% (69-99)		67% (22)		18% (6)	
Less than every day	32% (13-76)		23% (6)		0% (0)	
4 Week Engagement		p <.001*		p <.001*		p = .001*
Tracked every day (21)	98% (94-100)		86% (18)		29% (6)	
Less than every day	39% (20-81)		26% (10)		0% (0)	

*<.05 using Wilcoxon Rank Sum Test, Chi-Square (x2) Independence test, or a Fisher's Exact Test

Table 5 below shows that there were significant differences based on clinicals characteristics. Participants who did not have obesity had significantly higher median (IQR) engagement, compared to those that had it [94% (IQR: 74-99) vs. 64% (IQR: 27-93); p = .04]. There were no significant predictors based on sleep, blood pressure medication use, blood pressure medication nonadherence, WHO physical activity level, meeting WHO physical activity recommendation, blood pressure, or DASH score.

Table 5: Proportion of Engagement Based on Behavioral and Clinical Characteristics

	Overall Proportion of Engagement		80% Engagement		100% Engagement	
	Median Proportion of Engagment (IQR)	P Value	Proportion of Participants (N)	P Value	Proportion of Participants (N)	P Value
Sleep		p = .77		p = . 26		p = .38
Sufficient Sleep	82% (26-95)		53% (21)		8% (3)	
Insufficient Sleep	69% (29-93)		37% (7)		16% (3)	
BP Medication Use		p = .47		p = .24		p = .10
Yes	83% (66)		55% (16)		17% (5)	
No	71% (66)		40% (12)		3% (1)	
BP Medication Nonadherence		p = .15		p = .41		p = .28
Nonadherent	27% (13-96)		38% (3)		0% (0)	
Adherent	84% (54-98)		60% (12)		25% (5)	
WHO Physical Activity Level		p = .08		p = .37		p = .26
Low	57% (24-94)		40% (14)		6% (2)	
Medium	80% (29-95)		50% (7)		14% (2)	
High	93% (75-99)		67% (6)		22% (2)	
Meets WHO Physical Activity Recommendation		p = .11		p = .11		p = . 41
Meets Recommendation	85% (42-97)		57% (16)		14% (4)	
Does Not Meet Recommendation	51% (24-94)		37% (11)		7% (2)	
BMI		p = .04*		p = 0.09		p = .05
Has Obesity	64% (27-93)		40% (17)		5% (2)	
Does Not Have Obesity	94% (74-99)		65% (11)		24% (4)	
BP		p = .28		p = .57		p = 1.00
Elevated Blood Pressure or Greater	74% (27-93)		44% (18)		10% (4)	
Normal Blood Pressure	85% (39-98)		56% (10)		11% (2)	
DASH Score		p = .66		p = 1.00		p = 1.00
Less than 4.5	76% (32-95)		42% (25)		12% (6)	
Greater than or equal to 4.5	74% (17-96)		43% (3)		0% (0)	

*<.05 using Wilcoxon Rank Sum Test, Chi-Square (x2) Independence test, or a Fisher's Exact Test

Table 6 indicates that there were significant differences in the proportion of engagement based on psychosocial constructs. Participants who had a negative food environment perception had a significantly higher proportion of engagement, compared to those who had a positive perception 20% vs. 0%; (p = .02). There were no significant differences based on depression, extraversion, agreeableness, conscientiousness, neuroticism, openness, or health literacy.

Table 6: Proportion of Engagement Based on Psychosocial Characteristics

	Overall Proportion of Engagement		80% Engagement		100% Engagement	
	Median Proportion of Engagement (IQR)	P Value	Proportion of Participants (N)	P Value	Proportion of Participants (N)	P Value
Depression		p = . 39		p = . 44		p = . 40
Depressed	58% (24-95)		41% (9)		5% (1)	
Not Depressed	81% (36-94)		51% (19)		14% (5)	
Extraversion		p = .85		p = . 67		p = .40
High	79% (24-95)		50% (16)		6% (2)	
Low	74% (36-95)		44% (12)		15% (4)	
Agreeableness		p = . 67		p = . 94		p = .69
High	74% (27-94)		47% (16)		9% (3)	
Low	76% (29-95)		48% (12)		12% (3)	
Conscientiousness		p = . 67		p = . 52		p = 1.00
High	74% (24-94)		43% (13)		10% (3)	
Low	81% (39-95)		52% (15)		10% (3)	
Neuroticism		p = .48		p = .37		p = . 41
High	68% (24-94)		42% (13)		6% (2)	
Low	82% (37-96)		54% (15)		14% (4)	
Openness		p = .83		p = .54		p = 1.00
High	75% (31-94)		44% (14)		9% (3)	
Low	81% (25-98)		52% (14)		11% (3)	
Health Literacy		0.35		p = . 66		p = . 43
Adequate Health Literacy	75.6% (27-94)		46% (25)		9% (5)	
Limited Health Literacy	92% (59-99)		60% (3)		20% (1)	
Food Environment Perception		p = .09		p = .69		p = .02*
Negative Perception	80% (39-99)		50% (15)		20% (6)	
Positive Perception	76% (25-92)		45% (13)		0% (0)	

*<.05 using Wilcoxon Rank Sum Test, Chi-Square (x2) Independence test, or a Fisher's Exact Test

Notably, there also were trends among predictors that did not reach statistical significance. Those who were unemployed had a higher median (IQR) proportion of engagement, compared to those who were employed [92% (IQR: 29-94) vs. 68% (IQR: 27-93); p = .26]. Among participants taking blood pressure medications (N= 29), those who were adherent to talking their blood pressure medication had a greater median (IQR) proportion of engagement, compared to those who were nonadherent [84% (IQR:54-98) vs. 27% (IQR:13-96); p = .15]. The median (IQR) proportion of participants that met WHO physical activity recommendations had higher adherence, compared to those that did not meet recommendations [85% (IQR: 42-97) vs. 51% (IQR: 24-94);p = .11]. Similarly (See Table 6), those who were not depressed had higher median engagement, compared to those who were depressed [81% (IQR:36-94) vs. 58% (IQR: 24-95); p = .39]. Lastly, those who used apps had a higher median engagement, compared to those who didn't use apps [76% (IQR: 27-95) vs. 29%(IQR: 0); p = .41] Baseline DASH score did not predict engagement with self-monitoring.

4. Discussion

Engagement with self-monitoring is a key component of any intervention and its implications for behavior change are profound. Evidence suggests that those who have high engagement with self-monitoring are more likely to have better outcomes. (Bennett et al., 2018) (D. M. Steinberg et al., 2013) However, engagement has proven to be difficult, particularly when self-monitoring diet. As such, the DASH Cloud study sought to increase compliance to the DASH Diet through self-monitoring using mobile technologies. The study aimed to evaluate the efficacy of a dietary intervention that provided tailored, feedback, and skills training videos on how to adhere to the DASH diet, compared to self-monitoring alone. In this secondary analysis, we described patterns of dietary self-monitoring and characterized those who had the greatest engagement.

4.1 Principal Findings

Our results indicated that overall engagement was consistently high for the duration of the study. Engagement remained > 50% until weeks 10 and 12, but slightly waned during these weeks. Similarly, the proportion of those who had high engagement in each arm was ≥ 50% until Weeks 10 and 12, but declined in the intervention arm during these weeks. It is unclear why engagement fell below this threshold at these weeks. This is supported as the largest median difference of weekly self-monitoring between arms was at Week 8. After this week, the median monthly engagement and the proportion of those who had high engagement dramatically decreased in each arm, but particularly in the intervention arm. However, a notable finding we observed was that those who consistently self-monitored every day for the first 2 weeks, or first 4 weeks, successfully predicted those were more likely to have high overall engagement. During this first month, engagement was high even among those who didn't self-monitor every day, yet the consistency of daily tracking during this early period was important for maintaining high overall engagement.

In addition, those who had high overall engagement were more likely to have insurance, were married or living with a partner, did not have obesity, had a college degree, were somewhat comfortable with using apps, and were less likely to use an app for medication adherence. Those who had at least 80% engagement, were more likely to be married and somewhat comfortable with using apps and early engagement. Those who had 100% engagement had similar predictors, except comfort using apps and had a negative perception of their food environment. Among the limited evidence available about predictors of engagement with apps like the one we used in this study, gender is typically discussed as a significant predictor of self-monitoring behavior. (Hollis et al., 2008) However, since our study included only women, we were unable to determine if there was an association between gender and self-monitoring engagement.

4.1.1 Patterns of Self-Monitoring

Evidence shows that health apps have a propensity towards low self-monitoring rates, as most apps are only used once after they are downloaded, or discontinued after the tenth use. (Chen et al., 2015) As such, similar to other studies that have used apps, we observed that self-monitoring of behaviors decrease over time. (Gilson et al., 2016) (Guertler, Vandelanotte, Kirwan, & Duncan, 2015) (Glasgow et al., 2011) There is an inherent challenge of recording dietary intake, which may be further compounded by the complexity of using these apps. Since our study didn't target a population with high comfort with using apps or high usage of diet tracking apps at baseline, some users may have perceived the platform for the app as challenging to use, even if they felt comfortable navigating most apps. Although recent dietary apps have added features such as bar code scanners, dictation, or a recipe builder to ease the burden of tracking and use, the food registries used to enter food data are often invalid, unreliable, or missing data. (Arens-Volland, Spassova, & Bohn, 2015) In addition, they lack the ability to assist users with calculating the portion sizes of their meals, which can result in an inaccurate estimation of their caloric and nutrient intake. (Chen, Berkman, Bardouh, Ng, & Allman-Farinelli, 2019)

Another common issue with diet tracking apps is the number of foods missing from the food database on the back end of the app. (Cordeiro et al., 2015) Users have to then decide what is an appropriate replacement food if the one they consumed isn't available and this impacts the accuracy of the input reflecting actual intake. (Chen et al., 2019) Similarly, unless users precisely knew their portion size, they were more likely to report their food inaccurately. This shortcoming could have had the greatest effect on those who regularly cooked meals at home because entering each ingredient would be tedious and these users were more likely to have discrepancies with the app, which could have undermined their confidence with using it. (Chen et al., 2019) As such, despite its convenience and ease of use, using apps for dietary self-monitoring is still laborious and difficult to sustain for a long period of time, which may explain this downward trend. (Gill & Panda, 2015)

4.1.2 Frequency of Feedback

Self-monitoring is a nuanced behavior that behavioral researchers aim to further understand. However, studies suggest that there is value in providing tailored, individual feedback for dietary self-monitoring, as it can increase engagement and improve diet quality. (Acharya et al., 2011) Feedback improves engagement by increasing an individual's self-awareness and allows them to modify their habits based on their current progress. (Hermsen, Frost, Renes, & Kerkhof, 2016) Despite its benefits, the optimal content, timing and frequency of tailored feedback is still being explored. (Burke, Wang, & Sevick, 2011) As such, to prevent burdening the participant with mass text messages, we provided daily feedback for the first 2 weeks, then weekly feedback for the remainder of the study to the intervention arm. Although the effects of weekly feedback showed modest improvements in engagement, daily feedback may have had the greatest potential. (D. F. Tate, Jackvony, & Wing, 2006) We speculate that daily feedback is necessary for improving adherence to dietary self-monitoring because until week 4, the intervention arm had consistent, high engagement. However, this trend diminished and the attention control arm had greater engagement during weeks 5 through 12, as engagement in the intervention declined in parallel with the frequency of feedback. As the frequency of the feedback was reduced, participants may have had a reduction in motivation to track.

4.1.3 Content of Feedback

In addition, while the frequency of tailored, feedback may have been associated with self-monitoring adherence within the intervention arm, we are unable to fully explain why the attention control arm had higher engagement after week 5. Even though it was unexpected, it is possible that the feedback given to the intervention arm was unintentionally negative, instead of positive, or it lacked enough information to make it engaging for the user. For example, the intervention arm was given a score that represented the participant's compliance to the DASH Diet, but if achieving a high DASH score is difficult and it may be that individuals felt the feedback wasn't helpful enough to support DASH compliance. The feedback was specifically designed to be simple and straightforward, but it may be that participants needed more individualized feedback to support their dietary change efforts in order for full DASH compliance to be achieved. We speculate that this unintended consequence of providing this particular type of feedback, propelled disinterest and led to poor participant engagement. Furthermore, evidence suggests that those who are unlikely to accept the feedback are those who disagree with it, or view it as overwhelming. (Morrison, Moss-Morris, Michie, & Yardley, 2014) (Petty & Cacioppo, 1986) If participants in the intervention arm believed that the app inaccurately recorded their dietary intake, they may have lost confidence in the app and resisted feedback because they believed their DASH score should have been higher. Similarly, their score could have triggered a negative emotional response that reduced their motivation to change their behavior. (Bowen, Fries, & Hopp, 1994) Lastly, although the messages were tailored for each participant, those in the intervention could have assumed that the content lacked adequate personalization, or didn't have any at all. (Morrison et al., 2014) In contrast, since those in the attention control arm did not receive tailored feedback, they may have been more motivated because their feedback was subjective and based on how they perceived their progress. Their individual success, or compliance to the diet could have been measured based on their blood pressure at the end of the study.

4.1.4 Characteristics of Participants with High Engagement

A paucity of data exists that characterizes users that have high adherence to self-monitoring behaviors. However, similar to other studies, in this study we were able to establish some significant associations between educational attainment, BMI, marital status and self-monitoring, as those who had at least college degree, married or had a lower BMI were more likely to have greater engagement. (Kay et al., 2018) (Butryn, Phelan, Hill, & Wing, 2007) (Burke, Swigart, Turk, Derro, & Ewing, 2009) (Costa, Graça Pereira, & Pedras, 2012) In addition, we speculate that greater socioeconomic status is a driver for increased self-monitoring. This is corroborated by higher engagement among those with insurance and at least a college degree. Between these, the level of educational attainment may be the most important because it allows an individual to have greater employment opportunities, which can provide affordable insurance for health coverage. (Shavers, 2007) Similarly, greater access to care may prompt individuals to be more engaged in health-promoting behaviors because they are more aware of their health. (Shavers, 2007) This may help explain why those who had higher engagement were less likely to have obesity, had a negative perception about their food environment and were less likely to use an app to monitor their medication adherence. Furthermore, since this was digital health intervention, we expected participants to be comfortable with using apps, but it is unclear why those who were somewhat comfortable were more likely to have greater engagement. Since this was a subjective measurement of an individual's ability to navigate apps, participants may have inaccurately misclassified their ability and they were more comfortable than they reported they were.

4.1.5 Importance of Marital Support

Marital support was one of the strongest predictors of achievement of 80% and 100% engagement. Since behavior change is challenging and monitoring one's behavior is equally cumbersome, having a partner can potentially provide positive encouragement, accountability, and support with initiating and sustaining any type of behavioral intervention, or behavior change. (Burke et al., 2009) Couples can set goals together and motivate each other to meet them, which may lead to better health outcomes, than if done individually. (Lewis et al., 2006) Furthermore, by educating and including spouses in a treatment plan, they can learn of the implications of poor adherence and create a more conducive environment. (Costa et al., 2012) Although we didn't measure the support from spouses, our results show that their role may have be essential for meaningful engagement.

4.1.6 Early Engagement and Habit Formation

It is well-established that self-monitoring is arduous and adherence will decline over time. (Glasgow et al., 2011) However, when changing a behavior, if the necessary skills are provided to establish a consistent habit early-on, it can have a significant impact. (Gardner, Sheals, Wardle, & McGowan, 2014) The premise that consistent, early engagement is paramount for behavior change is indicated from this study. Our study saw that those who self-monitored 100% during the first 2 weeks, or 4 weeks, were significantly more likely to have high engagement overall. Similarly, other studies have found comparable findings, which observed that greater early self-monitoring adherence predicted a significant reduction in body weight, waist circumference, and body fat. (Williamson et al., 2010) (M. L. Patel, Hopkins, & Bennett, n.d.) (Harvey, Krukowski, Priest, & West, 2019) While the mechanism of how it improves behavioral outcomes has to be elucidated, behavioral interventions have proposed some explanations. These suggest that early adherence results in behavior change because it is a formative period that can engender sustainable habits through repetition, it improves self-efficacy and components of self-regulation, which were weak. (Williamson et al., 2010) (Lally, Jaarsveld, Potts, & Wardle, 2010) Since eating is a unconscious, reoccurring habit, dietary interventions should target the habit-formation of simple, attainable goals. (Gardner et al., 2014) The duration required for a habit to form is unclear, but evidence suggests it is approximately 66 days. (Lally et al., 2010) Our study indicates it could be approximately two weeks to a month, which is consistent with other studies that have shown that strong habits can form in as little as two weeks. (Gardner et al., 2014)

4.2 Implications for Policy and Practice

With a growing burden of cardiovascular disease in women, and men, in the U.S. and globally, there is value added from this study towards improving behavioral interventions for hypertension and other health behaviors. (Roth et al., 2017) More studies can focus on characterizing those who use technology for health and develop interventions that improve their adherence, or maintain their interest in self-monitoring.

More importantly, the findings from this study can be translated into clinical practice. Providers will have a better understanding of the barriers their patients face and will have the ability to treat patients more effectively because they will have this knowledge. (Ong, Chua, & Ng, 2014) Moreover, clinicians will have the ability to monitor their patients and provide clinically meaningful feedback in real-time, which may improve self-monitoring rates, particularly during the initiation of a behavior change. (Marzano et al., 2015) Considering the epidemiologic transition and the growing burden of non-communicable diseases, increasing the efficiency of health providers and health interventions is critical in managing chronic conditions.

4.3 Study Strengths and Limitations

Characterizing those who are "super-users" of technology to monitor their health remains elusive. (Meyer, Beck, Wasmann, & Boll, n.d.) However, this study helped better describe and predict those who are more likely to use technology to monitor their health, specifically their diet. Most notably, this study was able to distinguish the effects of early adherence to self-monitoring and its implications towards future digital health interventions.

Despite the novelty of this study, there were some key limitations that are worth noting. To begin, this was a feasibility study with a small sample size, so it is difficult to interpret the findings of this study because it wasn't powered to show an effect. As such, the associations that we observed could have been spurious findings. In addition, similar to other dietary studies, the accuracy of the data collected is subject to potential recall and response biases. Since participants were aware that their diet data would be collected, it may have led them to overestimate, or underestimate their diet. Similarly, since we defined a valid day of self-monitoring based on calorie intake, there may have been non-differential misclassification of participants. Participants may have logged one meal, or one food item to reach this threshold. Furthermore, the results of this study are not generalizable beyond the study population, which included mostly a White, educated sample and only included women. While it was not the intent of the study to have a predominately White sample, it suggests that recruitment strategies targeted a certain subset of women to participate in this study.

4.4 Implications for Further Research

This study provides a cursory understanding of how predominately White, educated, older women use their mobile phones to self-monitor their dietary behaviors and what predicts their adherence. Future studies should include a diverse sample, which includes men and all socioeconomic backgrounds to improve the generalizability of the results. By broadening the sample, behavioral scientists can develop more robust intervention strategies that are tailored to improve self-monitoring engagement among low users, and sustain engagement among high users. (Schoeppe et al., 2016) Using this data, the appropriate level of feedback, or content can be used for each individual, based on their needs. In addition, the mechanism of early adherence to self-monitoring should be further explored and its implications for long-term behavior change should be elucidated. Lastly, further tests such as trajectory, or latent class analysis should explore the predictors of self-monitoring. By employing more complex tests, it can provide a deeper understanding of the nuances associated with self-monitoring.

5. Conclusion

The results of this study indicate that marital status, lower BMI, higher education and early engagement were predictive of high self-monitoring engagement. However, the content and the frequency of the feedback given may influence levels of engagement. A follow-up study needs to be conducted that includes a larger, diverse, sample and compares daily feedback to weekly feedback, with different types of DASH diet related feedback. Most importantly, other predictors of self-monitoring should be elucidated, so that future studies can develop more robust interventions that target improving an individual's engagement, despite their engagement level. Given the high uptake of mobile technology, the implications of this study are profound.

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