PROMOTING ENGAGEMENT IN DIGITAL WEIGHT LOSS INTERVENTIONS

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A dissertation submitted to the faculty at the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Health Behavior in the Gillings School of Global Public Health.

Chapel Hill
2022

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ABSTRACT

Julianne Mary Power: Promoting Engagement in Digital Weight Loss Interventions
(Under the direction of Deborah F. Tate)

Obesity has reached epidemic proportions in the United States. Digital weight loss interventions are effective for weight loss, and engagement in digital weight loss interventions, especially self-monitoring, is crucial for success. Given that engagement with self-monitoring consistently declines over time, the purpose of this dissertation was to understand effective patterns of engagement with self-monitoring, as well as whether and to what extent novel approaches for simplified self-monitoring enhance intervention engagement. Aim One used latent class growth modeling with another mixture layer to identify groups of participants based on trajectories of engagement with self-monitoring of weight, diet, and physical activity among overweight or obese adults participating in an effective 12-month digital weight loss intervention (N = 363). Four engagement patterns emerged: never-engagers, low/declining engagers, early engagers, and sustained-engagers. Predicted percent weight loss was clinically significant at 12 months for both sustained-engagers (10.4%) and early engagers (5.1%), but not for low/declining (1.3%) or never-engagers (0.48%). Aim Two was a 3-month randomized controlled pilot trial that compared the feasibility and efficacy of simplified dietary self-monitoring targeting Red Food reduction (i.e. limiting high-calorie, high-fat foods) to simplified dietary self-monitoring targeting Green Food promotion (i.e. maximizing fruits, vegetables, lean proteins, etc.) on engagement with dietary self-monitoring, self-reported weight change, and dietary intake at 3 months among overweight or obese young adults (N = 60). There were no between-group differences in engagement with dietary self-monitoring over 3 months. A greater proportion of participants in the Red Food group (23.1%) achieved a clinically meaningful 5% weight loss compared with the Green Food group (0%). Diet quality significantly increased for participants in both groups, and there were no between-group differences in change over time. Simplified dietary self-monitoring targeting Green Food promotion may improve diet quality, however, limiting Red Foods appears to be a more effective simplified dietary self-monitoring strategy for weight loss. By understanding effective patterns of multiple measures of engagement with self-monitoring over time and exploring novel ways to promote greater engagement with dietary self-monitoring, this dissertation contributes to the body of research seeking to inform targeted efforts to promote sustained engagement with self-monitoring, which could improve the efficacy of digital weight loss interventions.

ACKNOWLEDGEMENTS

The authors thank Cathy Zimmer and Chris Wiesen for their important contributions to this research.

The authors thank the study participants for their important contributions to this research and acknowledge the staff involved in this project, including Karen Hatley, Kristen Polzien, Molly Diamond, and Chris Wiesen.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ADOPT	Alternative Dietary approaches Online to Promote Tracking
AIC	Akaike's Information Criterion
ASA24	Automated Self-Administered 24-Hour Recall
BIC	Bayesian Information Criteria
BMI	body mass index
CI	confidence interval
CONSORT	Consolidated Standards of Reporting Trials
DGA	Dietary Guidelines for Americans
E	entropy
ED	energy density
FV	fruits and vegetables
HEI	Healthy Eating Index
IQR	interquartile range
LCGM	latent class growth modeling
LRT	likelihood ratio test
N	population size
OR	odds ratio
PA	Physician Assisted
PCPs	primary care providers
PDA	personal digital assistant
PWL	percentage weight loss
SCT	Social Cognitive Theory
SD	standard deviation
SE	standard error

SSBIC	Sample Size Adjusted BIC
TFEQ	Three Factor Eating Questionnaire
TLD	The Traffic Light Diet
US	United States

CHAPTER 1: INTRODUCTION

Overview

More than 40% of U.S. adults are obese (Hales et al., 2020), increasing their risk of chronic disease (Field et al., 2001). Fortunately, weight loss of 5–10% of body weight can reduce disease risk (Wing et al., 2011). Digitally-delivered weight loss programs can be as effective as traditional face-to-face approaches in promoting weight loss (Thomas et al., 2019) and are more flexible, cost-effective, and have wider reach (Krukowski et al., 2011; Alamuddin & Wadden, 2016). Engagement in digital weight loss interventions has been positively associated with weight loss (Tate et al., 2006; Webber et al., 2008), but tends to decrease over time.

Engagement with self-monitoring of weight-related behaviors, including weight, physical activity, and diet, is crucial to the success of behavioral weight loss interventions and is associated with weight loss (Burke et al., 2011a). However, engagement with self-monitoring can be tedious and consistently declines over time (Burke et al., 2009). Despite technology that can promote engagement with self-monitoring (Burke et al., 2012), dietary self-monitoring remains particularly burdensome given the lack of digital tools that can automatically capture dietary data, such as an activity tracker for physical activity. Given the strong connection between dietary change and weight loss, it is important to understand ways to promote engagement with dietary self-monitoring, which may enhance the effectiveness of behavioral weight loss interventions.

The contribution of this dissertation is twofold: Aim One explores patterns of multiple measures of engagement with self-monitoring that emerge across participants in an effective online weight management intervention and identifies baseline characteristics and intervention outcomes associated with these patterns. Aim Two tests the effects of novel approaches for simplified dietary self-monitoring on engagement, diet quality, and resulting weight loss among young adults, a population at risk for poor dietary habits and vulnerability to weight gain (Williamson et al., 1990; Adams et al., 2014). This dissertation makes an important contribution to the literature on engagement in digital weight loss interventions by identifying patterns of engagement with self-monitoring that may require additional support to facilitate long-term engagement and achieve 5% weight loss. Additionally, this dissertation elucidates whether and to what extent simplified approaches for dietary self-monitoring promote engagement with monitoring. Findings shed light on ways to promote long-term engagement with self-monitoring, especially dietary self-monitoring, which could improve the efficacy of digital weight loss interventions.

Specific Aims

Aim 1: Quantify patterns of trajectories of multiple measures of engagement that emerge across participants in an effective online weight management intervention and identify baseline characteristics and intervention outcomes associated with these trajectory patterns.

Research Question 1.1: How many meaningfully distinct classes of engagement trajectories emerge over a 12-month, web-based weight loss intervention?

Research Question 1.2: Do participant baseline demographic characteristics predict trajectory classes?

Research Question 1.3: Do trajectory classes predict intervention outcomes at 12-months?

Aim 2: Develop and evaluate the effect of a 3-month mobile dietary intervention with a focus on weight loss designed to increase consumption of healthy foods ("green foods," i.e.

fruits, vegetables, etc.) that targets young adults on engagement with dietary self-monitoring and adherence to dietary goals at 3 months compared to a mobile dietary intervention designed to limit consumption of unhealthy foods ("red foods," i.e. high-calorie, high-fat), with secondary aims of evaluating weight change and change in diet quality at 3 months.

Primary Research Question 2.1: Will participants randomized to the green food intervention have greater engagement with dietary self-monitoring and adherence to dietary goals at 3 months compared to participants randomized to the red food intervention?

Hypothesis 2.1: Participants randomized to the green food intervention will have greater engagement with dietary self-monitoring and adherence to dietary goals at 3 months compared with participants randomized to the red food intervention.

Secondary Research Question 2.2: Will participants randomized to the green food intervention experience greater improvements in weight loss and diet quality at 3 months compared with participants randomized to the red food intervention?

Hypothesis 2.2: Participants randomized to the green food intervention will experience greater improvements in weight loss and diet quality at 3 months compared with participants randomized to the red food intervention.

Significance

Understanding patterns of engagement with self-monitoring over time, as well as predictors and outcomes associated with those patterns, could shed light on groups of individuals who are prone to low levels of engagement with self-monitoring in digital weight loss interventions, and who may require additional support to facilitate long-term engagement and achieve intended weight loss outcomes. Understanding whether and to what extent novel approaches for simplified dietary self-monitoring enhance intervention engagement, diet quality, and resulting weight loss could improve the efficacy of weight loss programs among young adults, a group that is at risk for poor dietary habits and vulnerability to weight gain. Understanding effective patterns of engagement in digital weight loss interventions, as well as effective dietary approaches that might facilitate engagement, will enable the development of effective and scalable treatment programs for obesity. This dissertation contributes to the field of electronic and mobile health by using a novel methodological approach to explore how patterns of multiple measures of engagement with self-monitoring over time are associated with health outcomes, which could be applied to digital behavior change interventions across a variety of behaviors and disease types. Additionally, Aim Two was delivered entirely remotely via mobile methods, which holds promise for dissemination across a wide range of populations.

CHAPTER 2: LITERATURE REVIEW

Obesity, defined as body mass index (BMI) of 30 kg/m^2 or greater, is considered an epidemic in the United States. Almost half (42.4%) of U.S. adults were obese in 2017-2018 (Hales et al., 2020). This statistic is concerning because obese individuals are at increased risk for chronic illnesses such as heart disease, stroke, diabetes, and cancer (Calle et al., 2003; Field et al., 2001). Obesity is also associated with higher all-cause mortality (Adams et al., 2006). Therefore, identifying effective strategies for obesity prevention and control is of great importance for public health.

Behavioral weight loss interventions reliably produce mean weight losses of 5–10% of initial body weight over 6 months (Alamuddin & Wadden, 2016), which is a clinically significant threshold for weight loss that can reduce cardiovascular disease risk (Wing et al., 2011). Behavioral weight loss interventions typically involve dietary change, increased physical activity, and behavioral therapy (Alamuddin & Wadden, 2016), and include a variety of intervention components, such as goal setting, problem solving, action planning, self-monitoring, and feedback (Tate et al., 2019). The standard behavioral program consists of weekly individual and/or group treatment sessions delivered in-person or by telephone, often for several months (Alamuddin & Wadden, 2016). Despite the demonstrated efficacy of such programs, they are not widely implemented because they require significant investments of time and cost (Krukowski et al., 2011).

Digitally delivered programs are promising because they are more flexible than the standard approach, have the potential for wider reach, and are more cost-effective (Krukowski et al., 2011; Alamuddin & Wadden, 2016). Such programs might include text messages to prompt self-monitoring and goal setting, weekly e-mail feedback, or a study website where participants can access study materials and self-monitoring diaries (Tate et al., 2001; Tate et al., 2006). Studies have demonstrated that digital weight loss programs can be effective in promoting weight loss (Thomas et al., 2019; Harvey-Berino et al., 2010). Harvey-Berino and colleagues (2010) conducted a 6-month randomized controlled trial that compared a behavioral weight loss program delivered via the Internet or in-person. They found that although the in-person treatment produced significantly greater weight loss, the Internet-based treatment still produced significant weight loss of 5.5 kg and the proportion of participants achieving 5% weight loss did not differ between groups (Harvey-Berino et al., 2010). Thomas and colleagues (2019) conducted an 18-month randomized controlled trial comparing a smartphone-based behavioral weight loss program to a standard group-based approach. They found that the smartphone-based program produced 5.5 kg weight loss while the group-based program produced 5.9 kg weight loss, which were not significantly different. These studies demonstrate that digital weight loss programs are comparable to traditional face-to-face approaches and can produce significant weight losses of more than 5 kg.

Engagement is a key component of efficacy in digital weight loss interventions (Eysenbach, 2005). There is no single, comprehensive definition of engagement, which limits our understanding of how engagement impacts behavior change (Danaher & Seeley, 2009; Cole-Lewis et al., 2019). Engagement has typically been operationalized as “usage” of digital interventions, focusing on temporal patterns (e.g. frequency, duration) and depth of usage (e.g. use of specific features) (Danaher et al., 2006; Perski et al., 2017). O’Brien and Toms’ (2008) definition of engagement focuses on interactions with intervention features and the quality of users' experiences, which provides insight into which features users enjoy or use the most. In the digital weight loss intervention literature, definitions of engagement vary and include but are not limited to: total number of visits, number of self-monitoring diaries completed, total number of posts, total time spent, as well as composite measures (Tate et al., 2006; Glasgow et al., 2007; Webber et al., 2008; Glasgow et al., 2011; Turner-McGrievy & Tate, 2013; Power et al., 2019). Studies have found positive associations between various measures of engagement and weight loss, suggesting that higher levels of engagement lead to greater weight loss in digital weight loss interventions (Tate et al., 2006; Webber et al., 2008; Turner-McGrievy & Tate, 2013; Power et al., 2019).

Relatively little is known about factors that predict engagement in digital weight loss interventions. Some studies have shown that participant characteristics, such as age (Turner-McGrievy & Tate, 2013), gender (Glasgow et al., 2007; Goh et al., 2015), and race/ethnicity (Demment et al., 2014) are associated with engagement patterns. Other studies have found no associations between engagement and participant characteristics (Glasgow et al., 2011; Power et al., 2019). Unick and colleagues (2019) found that greater boredom with weight loss efforts and greater temptation to eat foods inconsistent with weight loss goals were associated with early non-response in a digital weight loss intervention. More research is needed on a wider range of possible predictors to understand whether any variables reliably predict engagement in digital weight loss interventions.

A consistent finding in the literature is that engagement in digital weight loss interventions declines over time (Tate et al., 2006; Webber et al., 2008; Turner-McGrievy & Tate, 2013; Power et al., 2019). However, it is unclear whether this trend is necessarily detrimental to weight loss. Although sustained engagement over time is typically considered optimal, it could also signal a lack of success and dependence upon the intervention content (Yardley et al., 2016). Therefore, it is important to differentiate between disengagement from an intervention and sufficient mastery of intervention materials (Yardley et al., 2016; Bricker et al., 2018). Research has shown that there are qualitatively distinct patterns of engagement in digital interventions for weight loss and other health behaviors (Power et al., 2019; Glasgow et al., 2011; Donkin et al., 2013). In a secondary analysis of a Web-based postpartum weight loss intervention, Power and colleagues (2019) identified four different engagement patterns based on total number of website logins over 12 months, including non-users (0-11 logins), low-engaged (12-47 logins), high-engaged (48-96 logins), and super-users (97+ logins). In an Internet-based diabetes self-management intervention, Glasgow and colleagues (2011) found large variability in website use over 4 months based on summary usage variables, such as total website visits, time spent online, percent of days of self-monitoring, and number of page visits. In an online depression treatment trial, Donkin and colleagues (2013) identified low, medium, and high engagement patterns by trichotomizing usage metrics, including number of log-ins, modules completed, time spent online, and activities completed. Few studies have used longitudinal analytical methods to explore patterns of co-development of multiple measures of engagement in digital weight loss interventions over time. Examining multivariate engagement trajectories could elucidate individual response patterns across a wide range of intervention features and shed light on which engagement styles are most and least beneficial for weight loss, which could help to inform future program recommendations.

Engagement with self-monitoring of weight-related behaviors is integral to behavioral weight control programs (Burke et al., 2011a; Baker & Kirschenbaum, 1993; Steinberg et al., 2015; Goldstein et al., 2019). Burke and colleagues (2011a) conducted a systematic review on three components of self-monitoring in behavioral weight loss studies: diet, exercise, and self-weighing. They consistently found a significant association between self-monitoring these behaviors and weight loss (Burke et al., 2011a). Self-regulation theory posits that self-regulation efforts are more effective when individuals self-monitor and evaluate their current behavior compared to goals, which either encourages individuals to continue their current behavior or self-correct (Kanfer & Karoly, 1972). Individuals cannot self-regulate their behavior if they do not understand the conditions under which the behavior occurs or the consequences of the behavior. Hence, individuals are better able to self-regulate their behavior when they consistently engage with self-monitoring in temporal proximity to the target behavior (Bandura, 1991).

Dietary change accounts for most weight loss (Thomas et al., 2014; Thomas et al., 2012), and dietary self-monitoring has been consistently associated with weight loss in behavioral weight loss programs (Baker & Kirschenbaum, 1993; Burke et al., 2011a; Goldstein et al., 2019 Harvey et al., 2019). Burke and colleagues (2011a) found that across 15 behavioral weight loss studies that focused on dietary self-monitoring, there were significant associations between self-monitoring and weight loss, and higher completeness of self-monitoring records was associated with greater weight loss. In a secondary analysis, Goldstein and colleagues (2019) found that adherence to dietary self-monitoring in a behavioral weight loss program was associated with percent weight loss such that more days of self-monitoring corresponded to greater monthly weight losses during that month. In a 24-week behavioral weight control program that was delivered online, Harvey and colleagues (2019) found that frequency and consistency of dietary self-monitoring was significantly related to weight loss. These studies suggest that frequency, consistency, and completeness of dietary self-monitoring support weight loss in behavioral weight loss interventions.

Dietary self-monitoring can be tedious and time-consuming (Burke et al., 2009), and adherence tends to decline over time (Burke et al., 2011a). In a qualitative study, Burke and colleagues (2009) found that participants in a behavioral weight loss program managed the burden of dietary self-monitoring by limiting their choices to familiar foods with known calorie and fat content, however, this approach eventually led to boredom with eating the same foods (Burke et al., 2009). Digital tools, such as smartphone applications, can reduce the burden of dietary self-monitoring by automatically calculating calories consumed and tracking progress toward a specific calorie goal (Peng et al., 2016). Such tools promote adherence to self-monitoring and enable data collection and delivery of tailored feedback in real-time (Burke et al., 2011b, Burke et al., 2012; Carter et al., 2013; Beasley et al., 2008; Glanz et al., 2006). Burke and colleagues (2012) conducted a 24-month randomized controlled behavioral weight loss intervention comparing self-monitoring via a traditional paper diary or a personal digital assistant (PDA). They found that participants using the PDA exhibited significantly greater adherence to self-monitoring over time, and that weight loss was greater for those who were more adherent across groups (Burke et al., 2012). Carter and colleagues (2013) conducted a 6-month randomized controlled weight management pilot study comparing self-monitoring via smartphone app, website, or paper diary. They found that adherence to self-monitoring was higher in the smartphone group compared with the website and diary groups (Carter et al., 2013). These findings suggest that digital tools, especially via smartphone, can produce increased adherence to self-monitoring in behavioral weight loss interventions, which may enhance effectiveness.

Despite the advent of digital tools, engagement with dietary self-monitoring still declines over time (Power et al., 2019; Goh et al., 2015; Harvey et al., 2019). It is possible that calorie-counting, the traditional approach to dietary monitoring, is too burdensome for many participants given that calorie counting requires individuals to not only track all foods eaten, but also to understand the calorie content of those foods (Guth, 2018). A more simplified approach might only require individuals to monitor a subset of foods, such as foods to avoid (i.e. high-fat/high-sugar) or foods to consume more of (i.e. fruits/vegetables). The Traffic Light Diet (TLD) lends itself well to this approach because it categorizes foods into the colors of the stoplight: red, yellow, or green based on their calorie and nutrient content (Epstein et al., 2001). Green foods are high in nutrients and low in calories, while red foods are high in calories with low nutrient density. Previous use of the TLD in digital weight loss interventions has focused on limiting red foods, which has been effective for weight loss. Nezami and colleagues (2018) conducted a 6-month mobile intervention to reduce sugar-sweetened beverage intake among mothers and young children and instructed mothers to reduce their intake of red foods and self-monitor the number of times they consumed a red food each day. This approach yielded high engagement with self-monitoring, such that mothers monitored an average of 21.5 out of 24 weeks and was associated with 2.3 kg average weight loss at 6 months (Nezami et al., 2018). In another 6-month mobile weight loss intervention that compared traditional calorie monitoring to simplified monitoring of red foods using the TLD, there were no significant differences in weight loss or average daily caloric intake between the two groups (Nezami et al., 2022). Participants who monitored red foods lost 4.0% of body weight and 3.5 kg on average at 6 months (Nezami et al., 2022). This evidence suggests that mobile interventions using a simplified dietary approach in which participants monitor only a subset of foods using the TLD can be effective for weight loss and can promote sustained engagement with dietary self-monitoring over time.

Although restricting high-calorie red foods can be effective for weight loss, its impact on diet quality has not been well studied. Given that high diet quality can protect against major weight gain and risk of chronic diseases (Quatromoni et al., 2006), a simplified dietary approach that promotes diet quality could enhance weight loss and improve health. Dietary approaches that promote increased fruit and vegetable intake can lead to better diet quality and greater weight loss compared to dietary approaches that restrict high-calorie foods (Epstein et al., 2001; Ello-Martin et al., 2007; Rolls et al., 2004). Another benefit of this approach is that it focuses on what can be eaten rather than what cannot be eaten. A simplified dietary approach that focuses on the subset of foods that can be eaten, such as green foods in the TLD, could be equally if not more effective than a dietary approach that focuses on restricting red foods. However, no weight loss studies have compared the effects of these two simplified dietary approaches on engagement with dietary self-monitoring, diet quality, or weight loss.

Young adults are an ideal population in which to test this research question because young adulthood is associated with poor dietary habits and vulnerability to weight gain (Williamson et al., 1990; Adams et al., 2014). The prevalence of obesity among young adults aged 20-39 was 40% in 2017-2018 (Hales et al., 2020), and studies have shown that young adults are at risk for low engagement in Internet weight loss programs (LaRose et al., 2020). Additionally, approximately 95% of young adults in the U.S. own a smartphone (Pew Research Center, 2021). Thus, this population could benefit from mobile weight loss interventions utilizing simplified dietary self-monitoring strategies aimed at improving intervention engagement.

Summary

Almost half (42.4%) of U.S. adults are obese, including 40% of young adults aged 20-39. This is concerning because obese individuals are at greater risk for chronic illness and all-cause mortality. Behavioral weight loss interventions successfully produce mean weight losses of 5-10% of body weight, which can significantly reduce disease risk. Digitally delivered programs can be as effective as face-to-face programs but are more scalable and cost-effective. Engagement, especially with self-monitoring of weight-related behaviors, is necessary for success in digital weight loss interventions, however, engagement consistently declines over time. Research has detected qualitatively distinct patterns of engagement in digital weight loss interventions; however, little research has used longitudinal analytical methods to explore patterns of co-development of weight, diet, and physical activity self-monitoring over time. Understanding multivariate trajectories of engagement with self-monitoring in digital weight loss interventions could provide a broader picture of individual response patterns, as well as intervention outcomes associated with those response patterns, and inform future program recommendations. Additionally, given the strong connection between diet and weight, a critical next step in the literature is to understand how to promote engagement with dietary self-monitoring using novel approaches that are expected to increase adherence to tracking and dietary goals, which could enhance the efficacy of digital weight loss programs by improving both weight loss and diet quality.

CHAPTER 3: THEORETICAL FRAMEWORK

The interventions tested in Aim Two of this dissertation were based on the Boundary Model for the Regulation of Eating (Herman & Polivy, 1984), Social Cognitive Theory (McAlister et al., 2008; Bandura, 2004), and Self-Regulation Theory (Kanfer & Karoly, 1972). This study compared the feasibility and efficacy of two mobile dietary interventions on engagement with dietary self-monitoring, weight loss, and change in diet quality at 3 months among overweight or obese young adults. The interventions were identical except for the types of foods participants were instructed to self-monitor and the dietary goals participants were given. Each intervention used a simplified dietary self-monitoring strategy that was based on the Traffic Light Diet (TLD), which categorizes foods into the colors of the stoplight: red, yellow, or green based on their calorie and nutrient content (Epstein et al., 2001). Green foods are very high in nutrients and low in calories (low-energy dense), while red foods are higher in calories with low nutrient density (high-energy dense) (Epstein et al., 2001). In one intervention, participants were instructed to restrict red food consumption (≤3-7/day) and encouraged to self-monitor only red foods (red food group). In the other intervention, participants were instructed to consume more green foods (≥6-11/day) and encouraged to self-monitor only green foods (green food group). Although restricting red food consumption has been an effective approach for weight loss in past studies (Nezami et al., 2018; Nezami et al., 2022), no studies have compared the effects of these two simplified dietary approaches on engagement with dietary self-monitoring, diet quality, or weight loss.

Overview

According to the Boundary Model, food intake is regulated within the biological boundaries of hunger and satiety. Between these boundaries, where there is no biological pressure to eat, psychosocial variables, such as dietary restraint and disinhibition, can influence eating behavior. Dietary restraint is the conscious restriction of food intake to prevent weight gain or promote weight loss (i.e. dieting). Dietary disinhibition is the tendency to overeat in response to different stimuli, such as the presence of palatable foods or emotional distress. Individuals with a tendency toward dietary disinhibition may require higher levels of dietary restraint for successful weight control. Other psychosocial variables that may influence eating behavior are self-efficacy and self-regulation. Self-efficacy is the belief that one can exercise control over one's behavior, and self-regulation is the act of taking control and regulating one's own behavior. Self-monitoring of diet increases awareness of dietary behaviors, which promotes self-regulation and may increase dietary restraint and self-efficacy beliefs related to diet. Each construct, the theories from which they were derived, and their associations with total energy intake, diet quality, and weight loss, are described in more detail below.

Hunger and Satiety

The most basic drivers of eating behavior are hunger and satiety; organisms start eating when they're hungry and stop eating when they're full. However, research shows that non-physiological factors, such as social influence and cognitive pressures, also influence eating behavior. The Boundary Model for the Regulation of Eating accounts for both physiological and non-physiological determinants of eating behavior. The Boundary Model suggests that food intake is regulated within the physiological boundaries of hunger and satiety (Herman & Polivy, 1984). When individuals cross the lower boundary, or enter the aversive zone of hunger, they will eat to relieve the discomfort of hunger (Herman & Polivy, 1984). When individuals cross the upper boundary, or enter the aversive zone of satiety, they will stop eating to relieve the discomfort of satiety (Herman & Polivy, 1984). Between the physiological boundaries of hunger and satiety, there is no biological pressure to eat, which is known as the zone of biological indifference (Herman & Polivy, 1984). Within this zone, psychosocial variables exert their influence on eating behavior (Herman & Polivy, 1984).

Studies have found that subjective hunger self-ratings prior to a meal are significantly positively associated with the amount of food ingested (De Castro & Elmore, 1988; De Castro, 1996). Additionally, hunger has been associated with a lack of weight loss or with weight regain (Elfhag & Rössner, 2005). Food weight and volume serve as important regulatory signals for food intake, and research has shown that individuals become habituated to eating a constant weight of food (Poppitt & Prentice, 1996; Rolls & Bell, 2000). Therefore, hunger and satiety cues may be more sensitive to changes in food weight and volume than to the amount of energy consumed from foods (Poppitt & Prentice, 1996; Rolls & Bell, 2000). Food energy density (ED) is the amount of energy in food relative to its weight (kcal/g). Low-ED diets help lower energy intake without reducing total weight of food eaten, thereby promoting greater satiety than diets that restrict portions (Poppitt & Prentice, 1996). Low-ED foods, such as fruits and vegetables (FV), generally have high water content because water adds weight without adding energy (Rolls & Bell, 2000). High-ED foods generally have high fat content because fat has the highest ED (9kcal/g) relative to other macronutrients (4kcal/g) (Rolls & Bell, 2000). High-fat diets have also been shown to generate much lower satiety than diets that are high in carbohydrate or protein (De Castro, 1987; De Castro & Elmore, 1988). Therefore, eating more FV and less fat may help to control hunger by reducing dietary ED while allowing for consumption of a satisfying amount of food, thereby promoting satiety (Rolls & Bell, 2000; Rolls et al., 2005).

Low-ED diets have been associated with smaller BMI, lower hunger ratings, lower total energy intake, better diet quality, and weight loss (Vernarelli et al., 2018; Rolls et al., 2005; Ledikwe et al., 2007; Raynor et al., 2012; Ledikwe et al., 2006; Vadiveloo et al., 2018; Ello-Martin et al., 2007). In a secondary analysis of dietary data from participants in an 18-month randomized controlled weight loss intervention, Vadiveloo and colleagues (2018) found that increasing the number of low-ED foods consumed was associated with percent weight loss at 6 months, whereas decreasing the number of high-ED foods consumed was not. They also found that individuals who consumed both a high number of low-ED foods (≥6.6 per day) and a low number of high-ED foods (≤2 per day) experienced greater reductions in BMI and percent weight loss at 6 and 18 months than individuals who only met the high-ED target (Vadiveloo et al., 2018). Ello-Martin and colleagues (2007) conducted a clinical trial to test the effectiveness of two strategies to reduce dietary ED on body weight of obese women over 12 months; one group was told to reduce fat intake while the other group was told to reduce fat and increase FV intake. While both groups significantly reduced dietary ED, the reduce fat and increase FV group lost significantly more weight at 6 and 12 months compared with the reduce fat only group. Additionally, the reduce fat and increase FV group consumed significantly more food by weight daily, and reported significantly lower hunger ratings, than the reduce fat only group. These results demonstrate that a dietary approach that targets consumption of low-ED foods in conjunction with limiting high-ED foods promotes satiety and contributes to weight loss in the context of a weight loss intervention.

It is possible that targeting low-ED foods alone may be an equally effective dietary strategy to enhance weight loss and improve diet quality compared with targeting low-ED foods in conjunction with high-ED foods. Epstein and colleagues (2001) conducted a randomized controlled behavioral weight loss intervention for obese parents with children to test the effectiveness of two dietary approaches on parent and child eating behaviors and parent weight over 12 months. Parents were randomized to either increase FV intake (≥5 per day) or decrease intake of high-fat/high-sugar foods (≤10 per week). They found that parents in the increase FV group significantly increased FV intake and decreased consumption of high-fat/high-sugar foods (Epstein et al., 2001). Meanwhile, parents in the decrease fat/sugar group significantly decreased consumption of high-fat/high-sugar foods but showed no change in FV intake (Epstein et al., 2001). Parents in the increase FV group also showed significantly greater decreases in percentage of overweight, and lost approximately 5 kg more weight, than parents in the decrease high-fat/high-sugar group (Epstein et al., 2001). These results indicate that in the context of a behavioral weight loss intervention, a dietary approach that targets FV intake could be simpler and equally as effective as a dietary approach that targets both FV and fat intake. Increasing FV intake appears to simultaneously decrease fat intake, promoting greater weight loss than a dietary approach that targets fat intake alone (Epstein et al., 2001).

Beyond controlling hunger and promoting satiety, a dietary approach that encourages consumption of low-ED foods versus a dietary approach that restricts high-ED foods may make it easier to adhere to the dietary goals necessary for weight loss because it focuses on what can be eaten versus what cannot be eaten. Evidence suggests that food choices are motivated by emotional state; foods that are high in fat and sugar have been shown to activate the brain reward pathway, stimulating opioid release and reinforcing consumption of these foods to alleviate stress and improve mood (Adam & Epel, 2007; Gibson, 2006). Restricting consumption of high-ED foods (high-fat/high-sugar) may be a less effective strategy for weight loss than increasing consumption of low-ED foods because it requires behavioral inhibition. Repeatedly inhibiting motivated behaviors, such as eating a desired food in response to emotional distress, can create internal conflict and result in negative psychological and behavioral consequences, including behavioral excess in the form of overeating (Polivy, 1996; Polivy, 1998). The interventions in Aim Two were designed to decrease hunger and increase satiety by promoting greater intake of low-ED foods (green foods) and restricting intake of high-ED foods (red foods). Maximizing green food consumption may be a more effective and sustainable dietary approach than restricting red food consumption because it may simultaneously decrease red food consumption without requiring behavioral inhibition. There is little evidence to suggest that restricting high-ED red foods would simultaneously increase consumption of low-ED green foods, which promote satiety. Therefore, participants in the red food group may experience greater hunger than participants in the green food group.

Dietary Restraint

Dietary restraint is the conscious restriction of food intake (i.e. dieting) to prevent weight gain or promote weight loss. Restraint Theory, proposed by Herman and Mack (1975), suggests that eating behaviors vary by individual levels of dietary restraint such that unrestrained eaters respond more to “internal” or physiological cues to eat (i.e. caloric homeostasis), while restrained eaters respond more to “external” or cognitive cues to eat (i.e. the presence of attractive food cues). Hence, restrained eaters are more likely to overeat when cognitive control is disinhibited due to situational factors or emotional states (Herman & Mack, 1975). Building from Restraint Theory, the Boundary Model posits that there are individual differences in placement of the hunger and satiety boundaries, especially between restrained and unrestrained eaters. This model suggests that restrained eaters have a lower hunger boundary and a higher satiety boundary compared with unrestrained eaters (Herman & Polivy, 1984). This assumption is based on research showing that restrained eaters eat less than unrestrained eaters after an equivalent period of food deprivation, possibly resulting from conditioning to experience hunger (Herman & Polivy, 1984). Additionally, in certain situations, restrained eaters will eat much more than unrestrained eaters without any apparent signs of discomfort, a phenomenon known as counter-regulation (Herman & Mack, 1975; Herman & Polivy, 1984).

The Boundary Model's explanation for counter-regulation is that restrained eaters have a cognitively established diet boundary in addition to the physiologically established hunger and satiety boundaries (Herman & Polivy, 1984). This diet boundary represents a self-imposed limit for food intake on a given occasion and is set well below the point of true satiety. Once the diet boundary is perceived to have been crossed (i.e. the diet has been "blown"), there is no point in restraining further consumption and the restrained eater will eat substantially more food than the unrestrained eater, up to the point of true satiety (Herman & Polivy, 1984). The concept of a cognitively established diet boundary is supported by research showing that perceived rather than actual dietary violations induce overeating among restrained eaters (Polivy, 1976). A related explanation for counter-regulation is the limited capacity hypothesis, proposed by Boon and colleagues (2002), which suggests that overeating in restrained eaters results from cognitive capacity limitations. Supporting this hypothesis, Boon and colleagues (2002) found that restrained eaters ate the same amount as unrestrained eaters when they were not cognitively distracted but consumed more than the unrestrained eaters when they were distracted.

Dietary restraint has been associated with lower overall food intake, weight loss, and successful weight loss maintenance (De Castro, 1996; Lowe & Kleifield, 1988; McGuire et al., 2001). Additionally, not all restrained eaters tend to overeat (Lowe & Kleifield, 1988). One possible explanation for why restraint has been associated with both overeating and weight loss is that dietary restraint is not a unidimensional construct (Westenhoefer, 1991). Westenhoefer

(1991) administered the Three Factor Eating Questionnaire (TFEQ; Stunkard & Messick, 1985), commonly used to measure dietary restraint, to 54,525 predominately overweight participants during the second month of a 12-month computer-aided weight loss program. They found that the restraint scale of the TFEQ had two subscales, which they described as rigid control of eating (i.e. dichotomized, “all-or-nothing” approach to eating; not likely to compensate for dietary violations) and flexible control of eating (i.e. stopping eating, taking small helpings, eating slowly; more likely to compensate for unallowed foods). In testing the construct validity of these two subscales, Westenhoefer and colleagues (1999) found that higher flexible restraint was associated with lower BMI, while higher rigid restraint was associated with higher BMI. These findings suggest that dietary approaches that promote flexible restraint may be more effective for weight loss and weight loss maintenance than dietary approaches that promote rigid restraint.

Studies have shown that weight loss programs can increase flexible restraint (Bacon et al., 2002; Teixeira et al., 2010; Ello-Martin et al., 2007). Bacon and colleagues conducted a 1-year randomized controlled trial comparing a traditional “weight loss-centered” diet program to an alternative “health-centered” non-diet wellness program. They found that participants in the diet program lost a significant amount of weight and increased on measures of flexible restraint, while participants in the non-diet program did not lose weight and had no change on measures of flexible restraint (Bacon et al., 2002). In another 12-month randomized controlled behavior change intervention, Teixeira and colleagues (2010) found that increased flexible restraint mediated the relationship between the intervention and 12-month weight loss, as well as 24-month weight loss maintenance. These findings indicate that flexible restraint is an important mechanism for weight loss in weight management interventions. The interventions in Aim Two were designed to increase flexible restraint by encouraging participants to compensate for unallowed foods over the course of the week. However, restricting red foods may also promote rigid restraint because a restrictive dietary approach lends itself more to the "all-or-nothing" thinking characteristic of rigid restraint; if a participant exceeds her red food limit for the day, she may be more prone to dietary disinhibition than a participant who fails to meet her green food goal for the day. Therefore, restricting red foods may be a less effective dietary approach than maximizing green foods.

Dietary Disinhibition

Dietary disinhibition is the tendency to overeat in response to different stimuli, such as the presence of palatable foods or emotional distress. Until relatively recently, commonly used measures such as the Restraint Scale (Herman & Polivy, 1980) have confounded dietary disinhibition and dietary restraint (Wardle, 1986; Stice et al., 1997; Johnson et al., 2012). However, the introduction of the TFEQ (Stunkard & Messick, 1985) allowed researchers to differentiate these constructs. Studies have shown that higher levels of dietary disinhibition have been associated with higher BMI, higher energy intake, lower probability of successful weight loss, and weight regain after successful weight loss (Westenhoefer et al., 1999; Dykes et al., 2004; Wing et al., 2008). Therefore, dietary disinhibition may be a better predictor of weight gain than dietary restraint (Johnson et al., 2012; Dykes et al., 2004; Williamson et al., 1995).

The relationship between dietary disinhibition and weight appears to be moderated by restraint (Dykes et al., 2004; Williamson et al., 1995; Hays & Roberts, 2008). Dykes and colleagues (2004) conducted a cross-sectional analysis among 1470 women and found a significant interaction between restraint and disinhibition on body weight and size such that women in the low-restraint-high-disinhibition group were the heaviest and largest, while women in the low-restraint-low-disinhibition group were the lightest and smallest (Dykes et al., 2004). Williamson and colleagues (1995) also found an interaction between restraint and disinhibition in a cross-sectional study of 293 women. For individuals with higher disinhibition scores, dietary restraint attenuated the relationship between disinhibition and BMI, whereas for individuals with lower disinhibition scores, dietary restraint was not associated with BMI (Williamson et al., 1995). These results suggest that individuals with a tendency toward dietary disinhibition may require higher levels of dietary restraint for successful weight control (Johnson et al., 2012).

Further, rigid restraint has been positively correlated with disinhibition scores, whereas flexible restraint has been negatively correlated with disinhibition scores (Westenhoefer, 1991). This finding is consistent with the Boundary Model for the Regulation of Eating, which suggests that disinhibition occurs when a cognitively established diet boundary is crossed (Herman & Polivy, 1984). When there is no strict diet boundary (i.e. flexible restraint), disinhibition is less likely to occur (Johnson et al., 2012). Because rigid restraint is defined by an “all-or-nothing” approach to dieting, this approach is more vulnerable to the disinhibiting effect (Westenhoefer, 1991).

Studies have shown that weight loss programs can reduce dietary disinhibition (Teixeira et al., 2010; Dalle Grave et al., 2009; Ello-Martin et al., 2007). In a 1-year randomized controlled behavior change intervention, Teixeira and colleagues (2010) found that although disinhibition decreased in both the intervention and control groups, the decrease was larger in the intervention group. Additionally, significant decreases in disinhibition were associated with 12-month weight loss and 24-month weight loss maintenance in the intervention group (Teixeira et al., 2010). In a longitudinal study of obese patients participating in 12-month weight loss treatments at medical centers, Dalle Grave and colleagues (2009) found that successful weight loss was associated with reduced disinhibition, as well as increased dietary restraint. These findings indicate that decreased disinhibition may be critical for successful weight loss in weight loss interventions.

The interventions in Aim Two were designed to decrease dietary disinhibition by providing behavioral weight management lessons related to coping with aversive stimuli that may trigger overeating. However, if restricting red foods increases rigid restraint (as described above), participants in the red food group could be more vulnerable to dietary disinhibition than participants in the green food group.

Self-Regulation

Self-regulation, or the act of taking control and regulating one's own behavior, is an important construct in Social Cognitive Theory (SCT), which posits that individual, social and environmental factors interact in a reciprocal manner to explain behavior (McAlister et al., 2008; Bandura, 2004). Given rapid cultural change as well as constantly shifting social and environmental demands, individuals must develop the ability to self-regulate motivation and action to behave in a consistent way (Bandura, 1991; Bandura, 2005; Kanfer & Karoly, 1972). According to Bandura (1991), individuals cannot self-regulate their behavior if they do not understand the psychological and social conditions under which the behavior occurs, or the immediate and long-term consequences of the behavior. Hence, successful self-regulation depends upon consistent self-monitoring done in temporal proximity to the target behavior (Bandura, 1991). Self-regulation theory also suggests that individuals are better able to self-regulate behavior when they self-monitor and evaluate current behavior compared to goals, which either reinforces current behavior or allows for self-correction (Kanfer & Karoly, 1972). Similarly, Maes and Karoly (2005) describe self-regulation as a process aimed at the attainment and maintenance of personal goals. In their model, self-regulation occurs through several phases that involve goal commitment, action planning, feedback loops, and maintenance strategies (i.e. setting realistic outcome expectations) to help sustain goal attainment (Maes & Karoly, 2005; Bandura, 2005). Across theories and models, self-monitoring, goal setting, and feedback are critical for self-regulation of behavior. These components are also integral to successful weight loss interventions and have been shown to increase self-awareness of how behaviors impact weight (Baker & Kirschenbaum, 1993; Burke et al., 2011a). Greater engagement with self-monitoring in such interventions has also been associated with greater weight loss (Harvey et al., 2019; Power et al., 2019; Tate et al., 2006; Webber et al., 2008).

Researchers have theorized that people have a limited capacity for self-regulation (Muraven et al., 1998; Muraven & Baumeister, 2000; Baumeister et al., 2006). This is known as the strength model of self-control, which posits that people have a limited quantity of resources available for self-regulation and that self-regulation efforts, such as dieting, degrade over time (Muraven et al., 1998; Muraven & Baumeister, 2000; Baumeister et al., 2006). This model is based on three assumptions: 1) self-regulation efforts draw on some resource, leaving it depleted afterward (i.e. regulatory depletion); 2) successful self-regulation is dependent upon the availability of this resource, and; 3) all forms of self-regulation consume the same resource (Muraven et al., 1998). In support of these assumptions, Muraven and colleagues (1998) conducted a series of laboratory experiments and found consistently poorer performance on a second self-regulatory task resulting from having already performed a first self-regulatory task. According to this model, self-regulation resembles a muscle that becomes tired after exertion, but which can be strengthened through exercise, making people less prone to regulatory depletion (Muraven et al., 1999; Muraven & Baumeister, 2000; Baumeister et al., 2006). In another series of laboratory experiments, Muraven and colleagues (1999) found that participants who practiced exercises designed to increase their self-regulatory strength, such as keeping a food diary, demonstrated improved self-regulatory capacity after 2 weeks relative to a control group. They also found that participants who practiced more showed significant improvement in self-regulatory capacity relative to the control group, while participants who practiced less or did not practice at all over the 2-week intervention period did not differ from the control group (Muraven et al., 1999). Similarly, Oaten and Cheng (2006) found that participants who adhered to a regular physical exercise program for 2 months increased their self-regulatory capacity and improved on a wide range of regulatory behaviors relative to controls. These studies provide evidence that self-regulatory capacity 1) draws on the same resource and 2) can improve with practice over time.

Changes in self-regulation can contribute to dietary behavior change and weight loss (Stadler et al., 2010; Annesi, 2019). In a 24-month randomized controlled trial, Stadler and colleagues (2010) compared the effect of adding self-regulation training to an information-only intervention to promote FV intake among women. Self-regulation training included mental contrasting, a motivational technique that creates a strong goal commitment, and implementation intentions, which facilitate goal pursuit (Stadler et al., 2010). They found that adding self-regulation training increased intervention effectiveness; participants in the information + self-regulation group ate more servings of FV per week at 4-months, and significantly improved on FV intake from baseline to 24-months, compared with participants in the information-only group (Stadler et al., 2010). In a secondary analysis of women participating in community-based behavioral weight loss treatments, Annesi (2019) found that increased self-regulation skills significantly mediated the relationship between changes in FV intake and weight-related caloric intake over 6 months. These results indicate that self-regulation plays an important role in behavior changes related to weight loss. The interventions in Aim Two were designed to increase self-regulation by supporting daily self-monitoring of diet as well as adherence to daily dietary goals, and by providing weekly tailored feedback.

Self-Efficacy for Diet

Self-efficacy is a focal construct of SCT and is defined as the belief that one can exercise control over a health behavior across a variety of circumstances to produce desired changes (Bandura, 2004). Bandura (2004) argues that all personal change is rooted in self-efficacy beliefs, which impact behavior directly and shape goals, outcome expectations, and perceived barriers and facilitators related to behavior change. Stronger perceived self-efficacy yields more favorable behavior change outcomes, including greater perseverance in the face of barriers (Bandura, 2004).

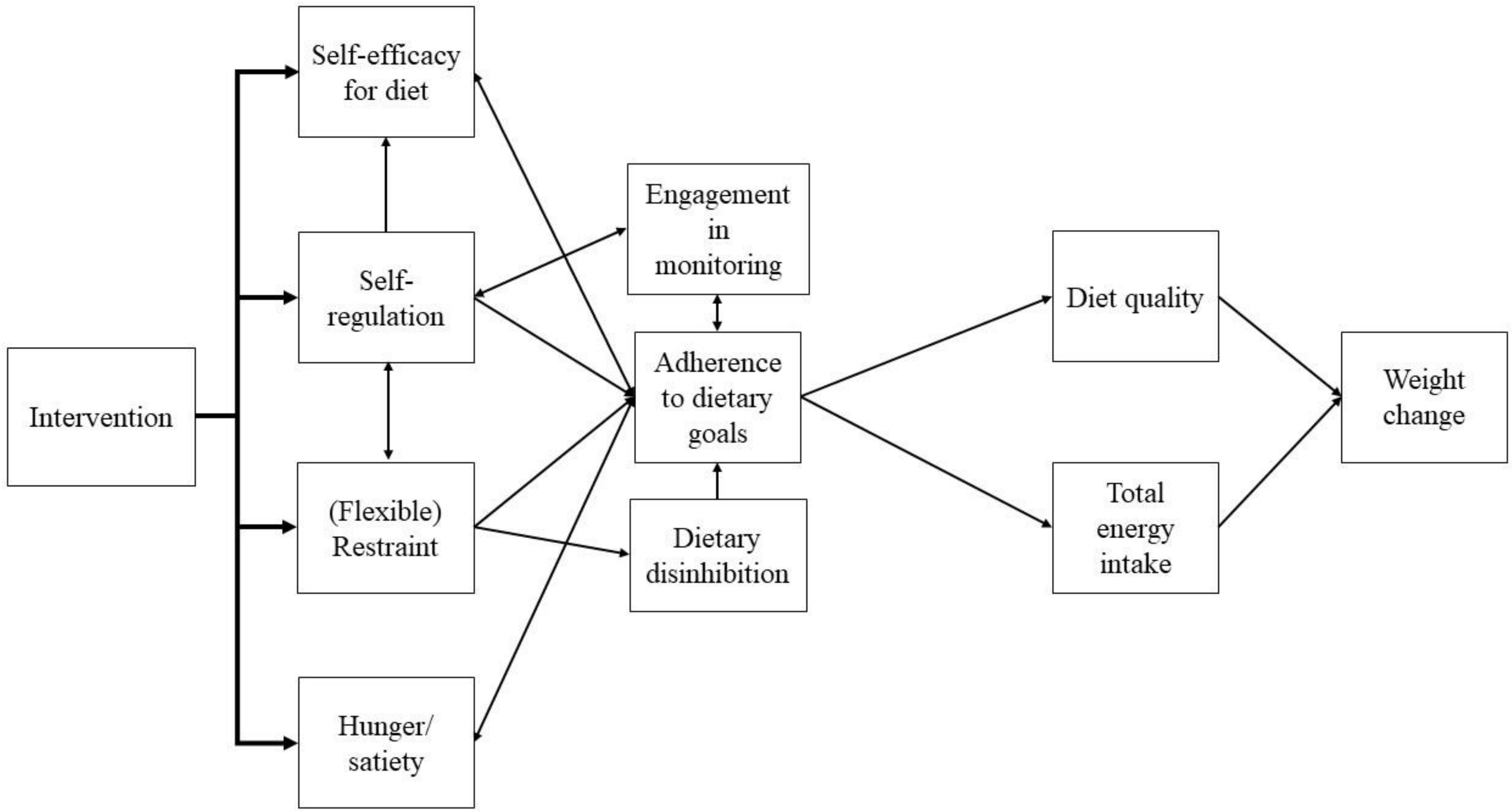
Self-efficacy appears to be an important mechanism for change in dietary behaviors (Shaikh et al., 2008). Spring and colleagues (2012) conducted a randomized controlled trial using mobile technology to test the effectiveness of different combinations of lifestyle recommendations on improving diet and physical activity behaviors over 3 weeks. They found that participants randomized to increase FV/decrease sedentary time achieved greater diet-activity improvement compared with other treatments. Additionally, increased self-efficacy for eating FV mediated the relationship between this treatment condition and increased FV intake at posttreatment (Schneider et al., 2016). Participants randomized to a more traditional weight loss approach (i.e. restrict fat/increase physical activity) achieved the least diet-activity improvement, and reported decreased self-efficacy for FV compared with other treatments (Schneider et al., 2016). This study suggests that traditional weight loss approaches may result in negative intervention effects and decreased self-efficacy for FV consumption. Similarly, in a 6-month randomized controlled weight loss intervention, Laing and colleagues (2014) found that self-efficacy for achieving weight loss goals decreased among intervention participants as compared with control participants at 3 months.

Traditional dietary approaches for weight loss, such as restricting fat, may undermine self-efficacy because of prior lack of success at maintaining weight loss. Alternative approaches, such as increasing FV, could be more empowering in terms of changing dietary behaviors. It is also possible that participants in weight loss interventions have an inflated sense of self-efficacy at baseline, resulting in decreased self-efficacy over the course of the intervention when faced with the challenges of performing weight loss behaviors in daily life. Some studies have shown that self-efficacy increases over the course of weight loss treatment (Clark et al., 1991; Pinto et al., 1999) and predicts subsequent weight loss (Edell et al., 1987; Jeffery et al., 1984). More research is needed to determine whether and to what extent different dietary approaches for weight loss impact self-efficacy for dietary change. The interventions in Aim Two were designed to increase self-efficacy for diet through daily self-monitoring and adherence to dietary goals as well as by providing positive reinforcement and encouragement through weekly feedback. However, the more traditional weight loss approach of restricting red food consumption could produce a negative intervention effect, resulting in decreased self-efficacy, especially among participants with previous weight loss attempts. It is possible that the more novel approach of maximizing green food consumption could produce larger increases in self-efficacy beliefs.

Conceptual Model

The interventions tested in Aim Two were developed using the Boundary Model for the Regulation of Eating (Herman & Polivy, 1984), Social Cognitive Theory (McAlister et al., 2008; Bandura, 2004), and Self-Regulation Theory (Kanfer & Karoly, 1972). Hunger/satiety, flexible restraint, self-regulation, and self-efficacy for diet were chosen as targets of change due to their specific associations with total energy intake, diet quality, and weight loss. First, the interventions will directly target hunger/satiety, flexible restraint, self-regulation, and self-efficacy for diet. Through decreased hunger and increased satiety, flexible restraint, self-regulation, and self-efficacy for diet, it is expected that participants will be more capable of adhering to the dietary goals prescribed by the interventions. Increased flexible restraint is expected to attenuate the effect of dietary disinhibition on total energy intake, and increased self-regulation is expected to yield greater engagement with self-monitoring, which will reciprocally increase self-regulation. Decreased dietary disinhibition and greater engagement with self-monitoring are also expected to increase adherence to dietary goals. In turn, adherence to dietary goals is expected to increase self-efficacy for diet, as well as satiety. Greater adherence to the dietary goals prescribed by the interventions is expected to result in improved diet quality and reduced total energy intake, thereby producing weight loss (Figure 3.1). It was hypothesized that participants in the green food group would have greater decreases in hunger and increases in self-efficacy at 3 months compared with participants in the red food group. Additionally, it was hypothesized that both groups would increase on flexible restraint at 3 months, however, participants in the red food group may also increase on rigid restraint and be more vulnerable to dietary disinhibition compared with participants in the green food group.

Figure 3.1 Conceptual model for aim 2



CHAPTER 4: PATTERNS OF SELF-MONITORING OVER TIME IN A RANDOMIZED CONTROLLED WEIGHT LOSS TRIAL: SECONDARY ANALYSIS OF MULTIVARIATE ENGAGEMENT TRAJECTORIES

Introduction

Over 70% of US adults have overweight or obesity (Fryar et al., 2020), putting them at increased risk for chronic illnesses such as heart disease, stroke, diabetes, and cancer (Calle et al., 2003; Field et al., 2001). Behavioral weight loss interventions reliably produce mean weight losses of 5–10% of initial body weight over 6 months (Alamuddin & Wadden, 2016), which is a clinically significant threshold for weight loss that can reduce cardiovascular disease risk (Wing et al., 2011). The standard behavioral program consists of weekly individual and/or group treatment sessions delivered in-person or by telephone, often for several months (Alamuddin & Wadden, 2016). Despite the demonstrated efficacy of such programs, they are not widely implemented because of the significant demands on time and cost (Krukowski et al., 2011). Digitally-delivered programs are promising because they provide more flexibility than the standard approach, have the potential to reach more individuals, and are more cost-effective (Krukowski et al., 2011; Alamuddin & Wadden, 2016). Studies have demonstrated that digital weight loss programs are comparable to traditional face-to-face approaches and can produce significant weight losses of more than 5 kg (Tate et al., 2003; Tate et al., 2006; Harvey-Berino et al., 2010; Thomas et al., 2019; Nezami et al., 2022). A meta-analysis by Beleigoli and colleagues (2019) found that digital interventions led to greater short-term weight loss than offline interventions among overweight and obese adults, however, high non-usage attrition rates across studies suggest that engagement is a major issue in digital interventions (Bennett and Glasgow, 2009; Neve et al., 2010).

Engagement is a key component of intervention efficacy (Eysenbach, 2005) and studies have found associations between engagement in digital behavior change interventions and improved health outcomes across a variety of behaviors and disease types (Bricker et al., 2018; Gold et al., 2007; Donkin et al., 2013; Glasgow et al., 2011; Hwang et al., 2013; Womble et al., 2004; Power et al., 2019). Engagement with self-monitoring of weight-related behaviors, such as diet, physical activity, and weight, is integral to behavioral weight control programs, whether digital or in-person (Burke et al., 2011a; Baker & Kirschenbaum, 1993; Steinberg et al., 2015; Goldstein et al., 2019). In internet-based weight loss interventions, participants who complete more self-monitoring diaries lose more weight (Tate et al., 2001, 2003, 2006; Webber et al., 2008). Burke and colleagues (2011) conducted a systematic review on three components of self-monitoring in behavioral weight loss studies: diet, exercise, and self-weighing. They consistently found a significant association between self-monitoring and weight loss (Burke et al., 2011). One possible explanation comes from self-regulation theory, which suggests that self-regulation efforts are more successful when individuals self-monitor and evaluate current behavior compared to goals, which either reinforces current behavior or allows for self-correction (Kanfer & Karoly, 1972; Bandura, 1991). However, engagement with self-monitoring in digital weight loss interventions consistently declines over time (Tate et al., 2006; Webber et al., 2008; Power et al., 2019; Tate et al., 2022).

Previous research has detected qualitatively distinct patterns of engagement in digital interventions for weight loss and other health behaviors based on basic site usage data such as logins, page views, average time spent on a page, etc. (Power et al., 2019; Glasgow et al., 2011;

Donkin et al., 2013). Power and colleagues (2019) identified four different engagement patterns based on overall number of website logins in a 12-month Internet weight loss intervention for postpartum women, including non-users (0-11 logins), low-engaged (12-47 logins), high-engaged (48-96 logins), and super-users (97+ logins). In an Internet-based diabetes self-management intervention, Glasgow and colleagues (2011) found large variability in website use over 4 months based on summary usage variables (i.e. total visits, time spent online, percent of days of self-monitoring, number of page visits). In an online depression treatment trial, Donkin and colleagues (2013) identified low, medium, and high engagement patterns by trichotomizing usage metrics (i.e. number of log-ins, modules completed, time spent online, and activities completed). The variable-centered approaches used in these studies, while useful for describing relationships among variables, are not focused on the relationships among individuals or individual response patterns. Grouping individuals based on individual response patterns, such that individuals within a group are more similar than individuals between groups, could be a useful approach for understanding how individual use of an intervention is associated with outcomes.

Latent class and growth mixture modeling are person-centered techniques that can be used to identify meaningful groups or classes of individuals within a larger heterogeneous population (Jung & Wickrama, 2008). Although there may not be actual "groups" of people that truly exist in the population, this statistical approach is a useful way of approximating unknown trajectories across population members. The current study uses latent class growth modeling (LCGM) with another mixture layer to identify groups of participants based on trajectories of engagement with self-monitoring of weight, diet, and physical activity among adults with overweight or obesity participating in an effective, 12-month digital weight loss intervention delivered through primary care. We also identify the predictors and outcomes associated with these trajectory patterns. Examining multivariate trajectories of usage over time could shed light on which usage patterns are most beneficial and help researchers make recommendations for future program use. This study will further our understanding of patterns of trajectories of self-monitoring of weight related behaviors that emerge over the course of an effective online weight loss intervention, how participant demographic characteristics predict these trajectory patterns, and how these patterns are associated with intervention outcomes.

Methods

Parent Study Design

Lose Now Physician Assisted (PA) was a group randomized controlled trial evaluating the effect of integrating two Internet weight loss programs into primary care compared to usual care with evaluation over 12 months. Detailed methodology is available elsewhere (Tate et al., 2022). Briefly, Lose Now PA targeted recruitment of 27 primary care providers (PCPs) and 550 patients ages 21-70 with a Body Mass Index (BMI) between 25-50 kg/m^2. Each PCP was randomly assigned to 1 of 3 treatment groups: 1) Enhanced Usual Care (i.e. received a 15-page booklet from the National Heart, Lung, and Blood Institute); 2) Internet weight loss; 3) Internet weight loss + PCP Feedback. Participants were assigned to the same treatment group as their PCP. Intervention participants were assigned a weight loss calorie goal based on their baseline weight that would allow them to lose 1-2 pounds per week (e.g., 1200-1800 kcals/day). Both intervention groups were more effective than enhanced usual care such that 12-month weight losses were -.92 kg for enhanced usual care, -3.68 kg for Internet weight loss, and -3.58 kg for Internet weight loss + PCP Feedback. Internet weight loss and Internet weight loss + PCP feedback lost significantly more weight than enhanced usual care but were not significantly different from each other. Results are described elsewhere (Tate et al., 2022).

Web-Based Intervention

The intervention included a comprehensive behavioral weight loss website with individualized goals for diet and physical activity that promoted 1-2 pounds weight loss per week. Upon the first login each day, participants were prompted to enter their weight from that morning or to indicate that they had not weighed themselves. This encouraged frequent weighing and allowed participants to closely track their weight. Participants were encouraged to weigh themselves at least once per week. Other website components included a self-monitoring diary, computer-tailored feedback, instructional lessons, a summary plan page and problem-solving tool, a goal setting tool, progress page, message board, and resource page. Additionally, an automated tailored progress email was sent to participants monthly and an optional live webinar was offered across groups bi-annually. The participants in Internet + PCP also received a biweekly, semi-automated, tailored email from their PCP regarding their adherence and weight loss. Participants received an automated email prompt each week alerting them to new content and reminding them to check-in to the website to report their weight, calorie intake and physical activity. To maximize flexibility in recording diet, participants could opt to use the website diary and enter all calories, an app or other diary of their choosing and enter summary calories for each day, or use a meal plan and enter only summary calories for each day and deviations or additions from the meal plan.

Participation rates did not differ between the two interventions on measures of average usage (median) nor the proportion of users logging in at a minimum frequency each month (1x per month) over time (Tate et al., 2022). Therefore, data for the current study included participants who were randomized to either intervention group (N=363).

Measures

Self-Monitoring Engagement. Number of days tracking weight, diet, and physical activity were calculated across 4 timepoints: 0-3 months, 4-6 months, 7-9 months, and 10-12 months. We used three month increments to allow for at least 4 timepoints to examine heterogeneity in growth trajectories of self-monitoring behaviors. Each weight, diet, and physical activity entry was time-stamped. Total number of tracking days for weight, diet, and physical activity were calculated by summing the number of days tracking data were entered into the website for each participant across the 4 timepoints. If a participant had no objective tracking data, number of tracking days was equated to 0 for that timepoint.

Covariates. At baseline, participants completed a demographic questionnaire assessing sex, age, race, and Type II diabetes status. Body weight was measured by research staff at the physician's office at baseline, 3 months, 6 months, and 12 months using a calibrated standard digital scale (Tanita Health Equipment, Arlington Heights, Illinois, USA). Two measures were completed with participants measured in light clothing without shoes. Height was measured at baseline using a wall-mounted stadiometer. Baseline BMI was calculated using participant height and weight. Percent weight loss was calculated at 3, 6, and 12-months.

Statistical Analyses

The aim of this analysis was to examine patterns of trajectories of engagement with self-monitoring of weight, diet, and physical activity over a 12-month digital weight loss intervention and identify the predictors and outcomes associated with these trajectory patterns. Latent class growth models were used to identify trajectories of weight, diet, and physical activity tracking. Then, we conducted a second layer mixture model to identify latent classes based on trajectory patterns across all three tracking behaviors. Finally, regression was used to examine associations between latent classes and demographic predictors as well as weight loss outcomes at 3, 6, and 12 months (Figure 4.1).

Separate LCGMs were estimated for weight, diet, and physical activity tracking over the 12-month intervention using Mplus version 8 (Figure 4.1). Latent class growth models generate a discrete set of prototypical trajectories which provide a semi-parametric summary of sample heterogeneity across individual trajectories. These models constrain within-class growth parameter (co)variances to zero and the analyst selects the most parsimonious latent class solution that is sufficient to recover most of the sample heterogeneity through between-class mean differences in growth parameters.

Before enumerating classes, we tested the polynomial order of each latent growth curve to determine the pattern of change over time (linear or quadratic). The overabundance of zeros in the data prevented the models from converging. Therefore, participants with a value of 0 at any time point were excluded from the LCGM analyses but were manually assigned to either a non-engagement trajectory class (0 for all timepoints) or an intermittent-engagement trajectory class (0 for at least one timepoint) for weight, diet, and physical activity tracking. Only participants with values greater than 0 tracking days at each timepoint for weight (N = 172; 195 or 53% excluded), diet (N = 85; 282 or 77% excluded), and physical activity (N = 101; 266 or 72% excluded) were included in the analyses to ease model estimation and detect heterogeneity amongst engagers. Variables were treated as continuous.

We constructed models ranging from two to four trajectory classes and model fit was evaluated using the following criteria: Akaike's Information Criterion (AIC), Bayesian Information Criteria (BIC), and Sample Size Adjusted BIC (SSBIC), with lower values indicating greater model parsimony. Due to the relatively small sample size, we did not enumerate more than four trajectory classes. The entropy index (values approaching 1 indicating clearer delineation of classes) was also used to describe the class solution and a parametric bootstrapped likelihood ratio test (LRT) was used to compare nested models (significant *p*-value indicates better fit of the model with more classes). The optimal class solution was selected based on the best-fitting model, interpretability of the class solution, and class sizes. After classes were identified, nominal variables indicating assigned trajectory class were created for weight, diet, and physical activity tracking (Figure 4.1).

To identify patterns of co-development of weight, diet, and physical activity tracking over the 12-month intervention, we conducted a second-layer mixture model using Mplus. We added participants with 0 tracking days at any time point back in at this layer. The second-layer mixture model allowed for the identification of latent classes (i.e. groups of individuals following similar development of self-monitoring behaviors over time) through finite mixture modeling. We constructed models ranging from three to five classes and assessed model fit using the criteria described above to determine the best fitting number of classes for our sample of participants. The resulting predicted group membership was treated as a grouping variable to identify demographic predictors and examine associations with intervention outcomes (Figure 4.1).

Full information maximum likelihood estimation was used to account for missing data. Categorical demographic predictors were dummy coded and multinomial regression was used to examine associations between demographic predictors and predicted group membership, with one group as the reference category. Predicted group membership was dummy-coded and linear regression was used to examine associations between predicted group membership and predicted percent weight loss at 12-months. We constructed four models with each level of predicted group membership as the reference category to make all possible comparisons for predicted percent weight loss between groups.

Results

Participant Characteristics

The subsample of intervention participants (N = 363; 73.3% female) initially aged 51.86 (SD = 10.86) years had an average BMI of 35.37 (SD = 5.49) kg/m^2 at baseline. Most participants were white, with 17.6% identifying as either Black (12.4%) or other race (5.2%). Twelve percent of participants reported having Type II diabetes at baseline. Average percent weight loss at 12 months was 3.34% (SD = 7.19) among completers (N = 318). There were no associations between participant characteristics and loss to follow-up at 12 months.

Latent Growth Curve Analyses

Weight Tracking. We tested the functional form of the growth curve and the quadratic model did not converge to a proper solution. Therefore, we used a linear model. A three-trajectory model emerged as the best fitting model among participants who engaged at each timepoint (n = 169, 46.6%) since a parametric bootstrapped LRT indicated that a three-trajectory model was a significantly better fit than the two-trajectory model (p < .001, Table 4.1). Although fit statistics improved marginally and a parametric bootstrapped LRT indicated that a four-trajectory model was a significantly better fit than the three-trajectory model ($p < .001$), entropy was higher for the three-trajectory model (E = 0.94), indicating clearer delineation of classes (Table 4.1).

The largest trajectory class (n = 83) was characterized by the lowest intercept and a slight decline over time, indicating a consistently low level of engagement with weight tracking (η_i = 23.05 days, SE = 1.67; η_s = -4.97, SE = 0.54). Another trajectory class (n = 51) was characterized by the highest intercept and a slight decline over time, indicating a consistently high level of engagement with weight tracking (η_i = 82.01 days, SE = 2.14; η_s = -3.25, SE = 0.81). The final trajectory class (n = 35) was characterized by a high intercept and a large negative slope, indicating a high starting level of engagement with weight tracking that was not sustained over time (η_i = 73.71 days, SE = 2.77; η_s = -21.04, SE = 1.10). A total of 194 participants were manually assigned to a trajectory class; n = 28 (7.7%) had 0 weight tracking days for all timepoints and were assigned to a non-engagement trajectory class while n = 166 (45.7%) had 0 weight tracking days for at least one timepoint and were assigned to an intermittent-engagement trajectory class.

Diet Tracking. The quadratic growth curve model did not converge to a proper solution. Therefore, we used a linear model. A three-trajectory model emerged as the best fitting model among participants who engaged at each timepoint (n = 82, 22.6%) since parametric bootstrapped LRTs indicated that a three-trajectory model was a significantly better fit than the two-trajectory model ($p < .001$), but a four-trajectory model was not a significantly better fit than the three-trajectory model ($p = .09$, Table 4.1). Although fit statistics were comparable and entropy was higher for the four-trajectory model (E = 0.95) compared with the three-trajectory model (E = 0.94), one trajectory class in the four-trajectory model had n = 2 (Table 4.1). Such a small class size indicates that the increase in the number of classes did not substantively express a different trajectory.

The largest trajectory class (n = 42) was characterized by the highest intercept and a slight decline over time, indicating a consistently high level of engagement with diet tracking (η_i = 85.98 days, SE = 1.39; η_s = -4.27, SE = 0.81). Another trajectory class (n = 21) was characterized by the lowest intercept and a moderate decline over time, indicating a consistently low level of engagement with diet tracking (η_i = 36.72 days, SE = 3.59; η_s = -8.64, SE = 1.31).

The final trajectory class (n = 19) was characterized by a high intercept and a large negative slope, indicating a high starting level of engagement with diet tracking that was not sustained over time (η_i = 84.89 days, SE = 3.22; η_s = -23.97, SE = 1.43). A total of 281 participants were manually assigned to a trajectory class; n = 90 (24.8%) had 0 diet tracking days for all timepoints and were assigned to a non-engagement trajectory class while n = 191 (52.6%) had 0 diet tracking days for at least one timepoint and were assigned to an intermittent-engagement trajectory class.

Physical Activity Tracking. The quadratic growth curve model did not converge to a proper solution. Therefore, we used a linear model. A three-trajectory model emerged as the best fitting model among participants who engaged at each timepoint (n = 98, 27.0%) since entropy was highest and a parametric bootstrapped LRT indicated that a three-trajectory model was a significantly better fit than a two-trajectory model ($p < .001$, E = 0.93, Table 4.1). Although fit statistics were comparable for the four-trajectory model and a parametric bootstrapped LRT indicated a significantly better fit for the four-trajectory model than the three-trajectory model ($p < .001$), one trajectory class in the four-trajectory model had n = 2 (Table 4.1) and therefore did not substantively express a different trajectory.

The largest trajectory class (n = 39) was characterized by the lowest intercept and a moderate negative slope, indicating a relatively low and declining level of engagement with physical activity tracking (η_i = 42.11 days, SE = 3.86; η_s = -11.70, SE = 1.31). Another trajectory class (n = 29) was characterized by the highest intercept and a near-zero slope, indicating a high sustained level of engagement with physical activity tracking (η_i = 72.79 days, SE = 4.12; η_s = 0.78, SE = 1.49). The final trajectory class (n = 30) was characterized by a high intercept and a moderate negative slope, indicating a relatively high but declining level of engagement with physical activity tracking (η_i = 61.70 days, SE = 3.52; η_s = -7.59, SE = 1.18). A total of 265 participants were manually assigned to a trajectory class; n = 106 (29.2%) had 0 physical activity tracking days for all timepoints and were assigned to a non-engagement trajectory class while n = 159 (43.8%) had 0 physical activity tracking days for at least one timepoint and were assigned to an intermittent-engagement trajectory class.

Second-Layer Mixture Model

Trajectories of engagement were similar across behaviors within the same class (Figure 4.2). A four-group model characterizing self-monitoring behavior co-development emerged as the best fitting model since AIC, BIC, and SSBIC improved, and entropy was the same as the three-group model (Table 4.2). Additionally, the parametric bootstrapped LRT indicated that a 4-group model was a significantly better fit than a 3-group model ($p < .001$), but the 5-group model was not a significantly better fit than the 4-group model ($p = .24$) (Table 4.2). The largest subgroup (n = 176, 48.5%) was labeled low/declining-engagers because they were characterized by relatively low average tracking days at time 1 that declined to near-zero average tracking days by time 4 across all three behaviors (Figure 4.2). One subgroup (n = 82, 22.6%) was labeled never-engagers owing to their near-zero or zero average tracking days at each timepoint across all three behaviors (Figure 4.2). A smaller subgroup (n = 47, 12.9%) was labeled early-engagers because of their relatively high average tracking days at time 1 that moderately declined by time 4, but never reached zero average tracking days at any timepoint across all three behaviors (Figure 4.2). Finally, another subgroup (n = 58, 16.0%) was labeled sustained-engagers because they were characterized by consistently high average tracking days that only slightly declined over time across all three behaviors (Figure 4.2).

Predictors of Engagement with Self-Monitoring

The low/declining-engager group was used as the reference category because almost half of participants (48.5%) fell into this group. The odds of being in the sustained-engager group relative to the low/declining-engager group increased by a factor of 1.06 for every year increase in age, controlling for all other covariates (OR = 1.06, $p < 0.001$,). Controlling for all other covariates, the odds of being in the never-engager group relative to the low/declining-engager group increased by a factor of 3.91 for participants who identified as a race other than white or Black (OR = 3.91, $p = 0.01$). The odds of being in the early-engager group relative to the low/declining-engager group decreased by a factor of 0.88 for every 1 unit increase in BMI at baseline, controlling for all other covariates (OR = 0.88, $p = 0.001$). There were no other significant associations.

Self-Monitoring and Weight Loss

The model explained 31% of variance in percent weight loss at 12 months ($p < .001$). Controlling for covariates, sustained-engagers had significantly greater percent weight loss at 12 months compared with all other groups (Table 4.3). These differences were also significant at 3 and 6 months. Early-engagers had significantly greater percent weight loss at 12 months than low/declining-engagers and never-engagers (Table 4.3). These differences were also significant at 3 and 6 months. Percent weight loss at 12 months was not significantly different between low/declining-engagers and never-engagers (Table 4.3). However, at 3 and 6 months low/declining-engagers had significantly greater percent weight loss than never-engagers. Controlling for covariates, average predicted percent weight loss at 12 months was 10.4% (SE = 1.05) for sustained-engagers and 5.1% (SE = 0.96) for early engagers (Figure 4.3). Average predicted percent weight loss at 12 months was less than 2% for both low/declining-engagers and never-engagers at 1.30% (SE = 0.42) and 0.48% (SE = 0.76), respectively (Figure 4.3).

Discussion

The objective of this study was to examine multivariate trajectories of engagement over 12 months in an effective online weight loss intervention using a novel data-driven approach to identify meaningful groups of individuals based on their individual patterns of engagement. This study identified four distinct groups of self-monitoring trajectories: (1) never-engagers, characterized by near-zero or zero average tracking days at each timepoint; (2) low/declining-engagers, characterized by low average tracking days at time 1 that declined to near-zero average tracking days by time 4; (3) early-engagers, characterized by high average tracking days at time 1 that moderately declined by time 4, but never reached zero average tracking days at any timepoint; and (4) sustained-engagers, characterized by consistently high average tracking days that only slightly declined over time. Average predicted percent weight loss was clinically significant at 12 months for both sustained-engagers (10.4%) and early engagers (5.1%), but not for low/declining (1.3%) or never-engagers (0.48%). Results from this exploratory analysis provide evidence that individual engagement patterns for self-monitoring are similar across behaviors and can predict treatment response. Continued research on patterns of engagement over time with other intervention components, such as lesson page views, visits to the problem-solving tool, or posts to the message board could provide a more comprehensive view of individual engagement patterns across intervention features that can predict weight loss.

Similar patterns of engagement over time have been identified in other digitally-delivered interventions for weight management. Demment and colleagues (2014) used latent class analysis to identify engagement trajectories in an online intervention to prevent excessive gestational weight gain during pregnancy, including "super-users" (i.e. high and consistent usage of all intervention features), "medium-users" (i.e. almost consistent use of weight tracker and high use of other intervention features), and "non-users" (i.e. never engaged with intervention features).

Goh and colleagues (2015) used latent-class growth modeling to identify engagement trajectories in an 8-week diabetes self-management intervention delivered via a smartphone app, including “consistent users” (i.e. weekly use throughout all or most of the 8 weeks), “intermittent-waning users” (i.e. occasional weekly use mainly in the first 4 weeks), and “minimal users” (i.e. no app use at all or use only in the first 2 weeks). Lavikainen and colleagues (2022) used latent class growth models to identify engagement trajectories over 12 months with an app designed to prevent type 2 diabetes, including “daily usage,” “twice weekly usage,” “weekly usage,” and “terminated usage” (i.e. few usage days in the first months dropping close to zero after 6 to 7 months). To ease comparison across studies, future research could synthesize engagement patterns identified in the literature.

The proportion of participants categorized into these engagement patters is also similar across studies. Across studies, a small group of “consistent” users characterized by high and consistent engagement emerged. In the current study, sustained-engagers accounted for 16% of the sample, compared to 13% (“super-users,” Demment et al., 2014), 9.5% (“consistent users,” Goh et al., 2015), and 15.1% (“twice weekly” and “daily usage,” Lavikainen et al., 2022). A similar group of “non-users” characterized by no use or minimal engagement also emerged. In the current study, never-engagers accounted for 22% of the sample, compared to 20% (“non-users,” Demment et al., 2014). Across studies, most participants are categorized into a “minimal” engagement category characterized by overall low or occasional engagement in the first few weeks of the intervention. Demment and colleagues (2014) found that 38% of their sample were categorized as “almost consistent” and “inconsistent” weight trackers. In the current study, low/declining engagers accounted for 48.5% of the sample, compared to 46.9% (“terminated usage,” Lavikainen et al., 2022) and 78.6% (“minimal users,” Goh et al., 2015). Given the high proportion of participants categorized into the “minimal” engagement category across studies, future research could explore possible heterogeneity within this group, such as participant characteristics and outcomes on intervention targets.

Greater engagement with self-monitoring was associated with more favorable weight loss outcomes over 12 months, which is consistent with engagement findings from other Internet-based weight loss interventions (Power et al., 2019; Funk et al., 2010; Hunter et al., 2008; Krukowski et al., 2008; Tate et al., 2006; Tate et al., 2003). In the current study, low/declining engagers (48.5% of the sample) did not achieve 5% weight loss at 12 months, whereas early-engagers (13% of the sample) did achieve clinically significant weight loss. In both groups, engagement decreased over time. However, on average early-engagers engaged at each timepoint whereas low/declining engagers did not, especially at timepoints 3 and 4, which may account for the significant difference in weight loss between the groups at 1 year. In a systematic review to conceptualize engagement in digital interventions, Perski and colleagues (2017) suggest that there may be a pre-defined level of engagement at which an intervention is effective (i.e. “optimal dose”). It is possible that participants in the early-engager group achieved an “optimal dose” of self-monitoring that resulted in clinically significant weight loss, whereas low/declining engagers did not. Perski and colleagues (2017) also suggest that an “unmeasured third variable” may be responsible for the observed association between increased engagement and positive intervention outcomes. In the current study, participants with higher BMI were significantly less likely to be in the early-engager class relative to the low/declining-engager class. Therefore, it is also possible that individuals with higher BMI may need more support to sustain engagement with self-monitoring.

Age and race were also associated with likelihood of engagement class membership. Relative to the low/declining-engager class, older participants were more likely to be in the sustained-engager class. Similarly, Glasgow et al. (2007) and Lavikainen et al. (2022) found that older participants were more likely to demonstrate ongoing engagement in digital interventions for weight loss and type 2 diabetes prevention, respectively, and other studies have shown young adults to be at risk for low engagement (LaRose et al., 2020). Minority race has been associated with lower levels of engagement. In the current study, participants that identified as a race other than white or Black were more likely to be in the never-engager class relative to the low/declining-engager class. Glasgow and colleagues (2007) found that African Americans were less likely to demonstrate ongoing engagement in an Internet-based weight loss program. Blackman Carr and colleagues (2018) also found that African American women had significantly fewer website log-ins compared with Non-Hispanic White women in a 4-month randomized controlled trial based on the Diabetes Prevention Program. Although the current study did not examine associations between psychosocial constructs and engagement, other studies have found associations between engagement and baseline motivation levels (Glasgow et al., 2007), baseline self-efficacy scores (Glasgow et al., 2007), exercise motivation scores (Goh et al., 2015), and baseline diet quality (Lavikainen et al., 2022). Future interventions could include adaptive components for lapses in engagement, such as meetings with a counselor, to improve outcomes among groups that are less likely to engage long-term.

Strengths of this study include a powerful data-driven analysis that identified true usage patterns based on multiple trajectories of engagement with self-monitoring over 12 months. Additionally, self-monitoring data was captured automatically from the website interface. Limitations include a relatively small sample size (N = 363), especially for participants with engagement data at each timepoint, which yielded small class sizes in the latent growth curve analyses. Participants who engaged at some but not all timepoints were manually assigned to an intermittent-engagement trajectory class for weight (45.7% of participants), diet (52.6% of participants), and physical activity (43.8% of participants) tracking. Hence, the latent growth curve models did not distinguish potential heterogeneity in engagement patterns over time within the intermittent-engagement trajectory class for each behavior. Finally, the mode of self-monitoring was the same across all three behaviors (i.e. participants entered their information in the self-monitoring diary on the intervention website), which may explain why individual engagement patterns for self-monitoring were similar across behaviors. Future studies could examine whether varying engagement patterns emerge across behaviors using different modes of self-monitoring, such as a digital scale for weight tracking, an app-based food log for diet tracking, and a wearable device for physical activity tracking. Research recommendations include exploring usage patterns based on multiple trajectories of engagement with other intervention features, synthesis of engagement patterns over time across studies, and further examination of heterogeneity in engagement patterns within the “minimal” or “intermittent” engagement category.

Table 4.1 Fit statistics for latent growth curve models

Self-Monitoring Behavior[a]	**Trajectory Class N**	**AIC**	**BIC**	**Sample-Size Adjusted BIC**	**Entropy**	**Parametric Bootstrapped LRT**
Weight (N=169)						
2 Class Trajectory Model	1 = 116 2 = 53	5648.59	5686.15	5648.15	0.97	
3 Class Trajectory Model	1 = 35 2 = 83 3 = 51	5580.92	5627.87	5580.37	0.94	<0.001
4 Class Trajectory Model	1 = 23 2 = 33 3 = 33 4 = 80	5555.52	5611.86	5554.87	0.92	<0.001
Diet (N=82)						
2 Class Trajectory Model	1 = 47 2 = 35	2806.65	2835.54	2797.69	0.96	
3 Class Trajectory Model	1 = 42 2 = 21 3 = 19	2768.42	2804.52	2757.21	0.94	<0.001
4 Class Trajectory Model	1 = 20 2 = 2 3 = 19 4 = 41	2765.31	2808.63	2751.86	0.95	0.09
Physical Activity (N=98)						
2 Class Trajectory Model	1 = 60 2 = 38	3395.86	3426.88	3388.99	0.84	
3 Class Trajectory Model	1 = 30 2 = 39 3 = 29	3380.17	3418.94	3371.57	0.93	<0.001
4 Class Trajectory Model	1 = 2 2 = 22 3 = 34 4 = 40	3369.88	3416.41	3359.57	0.91	<0.001

[a]Participants with 0 engagement at any timepoint were excluded from latent growth curve analyses and manually assigned to a latent growth curve class

Table 4.2 Fit statistics for second-layer mixture model (N = 363)

Class Solution	Mixture Class N	AIC	BIC	Sample-Size Adjusted BIC	Entropy	Parametric Bootstrapped LRT
3 Group Model	1 = 82 2 = 173 3 = 108	2253.13	2401.12	2280.56	0.96	
4 Group Model	1 = 176 2 = 82 3 = 47 4= 58	2163.37	2361.98	2200.18	0.96	0.00
5 Group Model	1 = 58 2 = 176 3 = 82 4 = 17 5 = 30	2177.07	2426.31	2223.27	0.95	0.24

Table 4.3 Differences in predicted percent weight loss at 12 months controlling for sex, age, race, Type II diabetes status, and baseline BMI

Self-Monitoring Group	**Never-engagers as reference group B (Std Err)**	**Low/declining engagers as reference group B (Std Err)**	**Early engagers as reference group B (Std Err)**	**Sustained-engagers as reference group B (Std Err)**
Never-engagers		0.83 (0.86)	4.64 (1.25)*	9.94 (1.29)*
Low/declining engagers	-0.83 (0.86)		3.81 (1.07)*	9.11 (1.15)*
Early engagers	-4.64 (1.25)*	-3.81 (1.07)*		5.30 (1.37)*
Sustained-engagers	-9.94 (1.29)*	-9.11 (1.15)*	-5.30 (1.37)*	
Model R-Squared	0.31			

*p is significant at .05 level

Figure 4.1 Conceptual model for aim 1

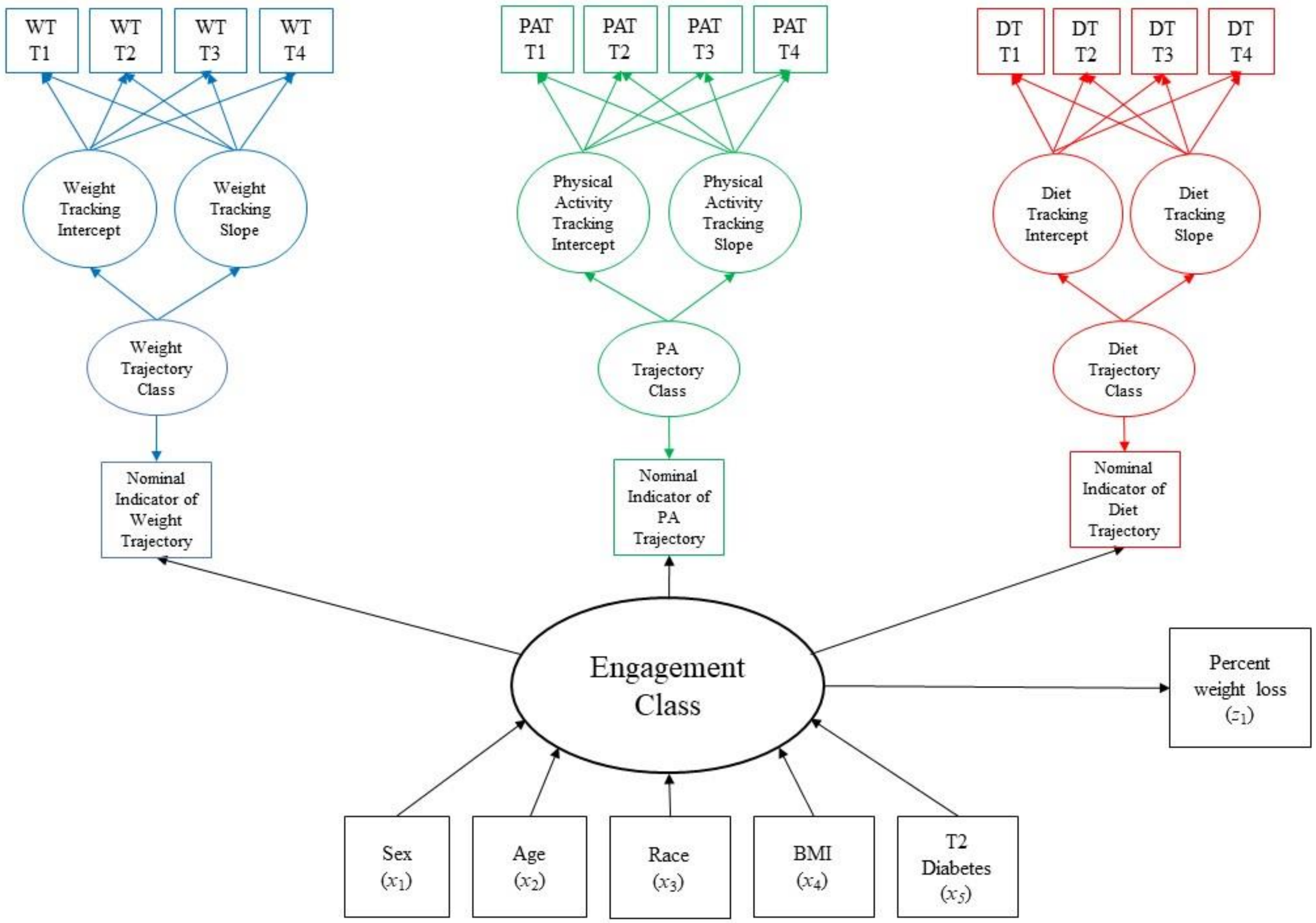


Figure 4.2 Average tracking days for weight, diet, and physical activity by group

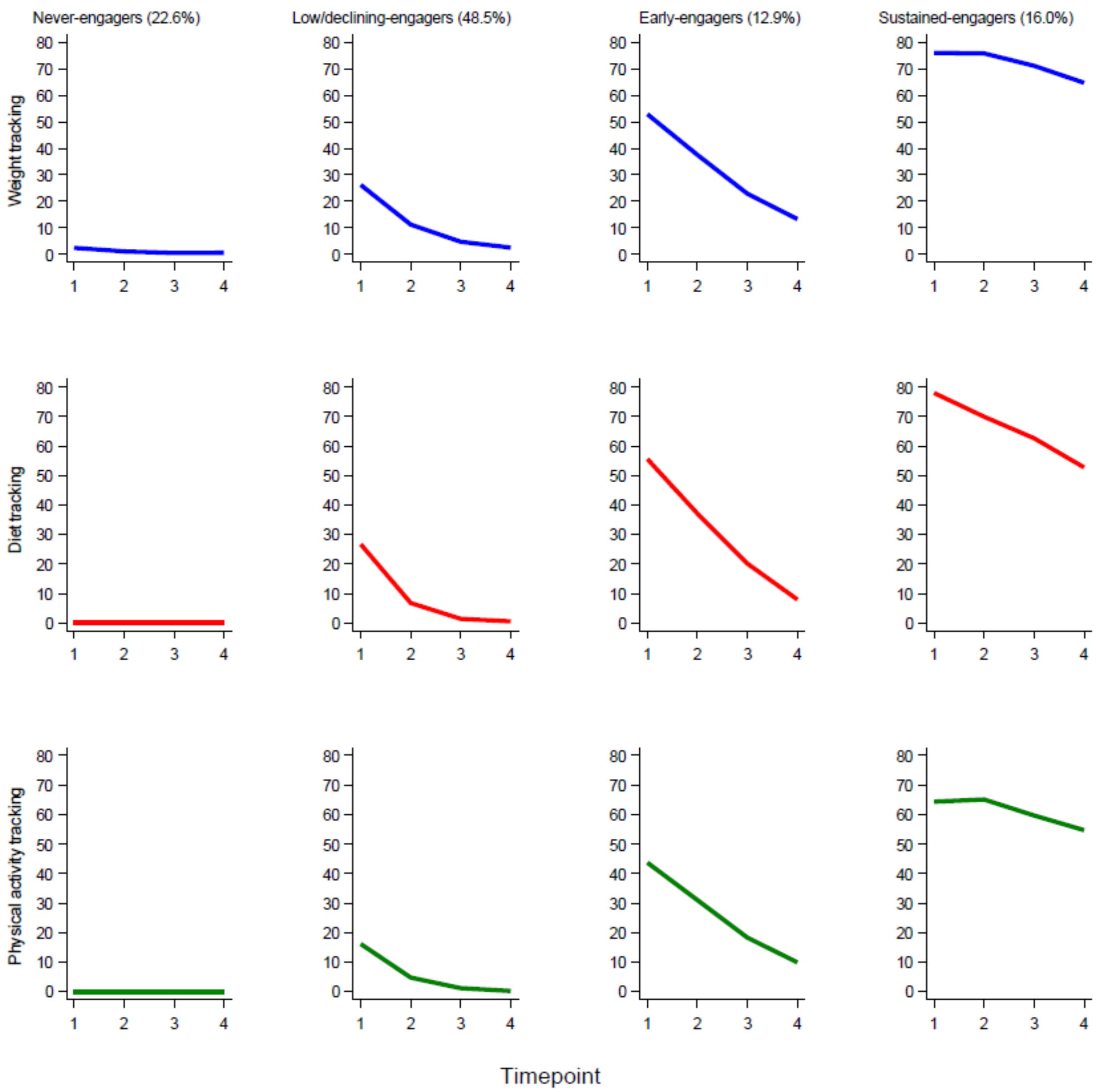
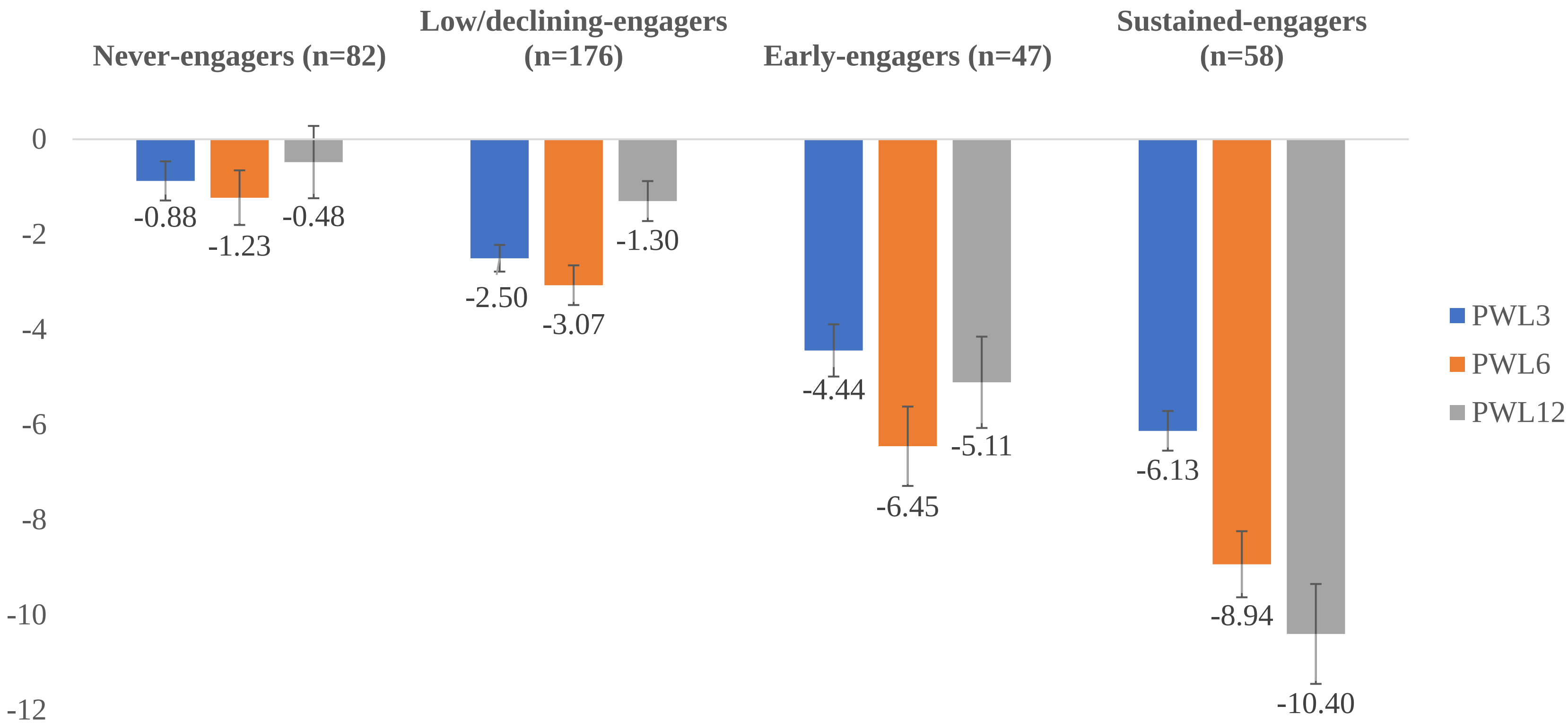


Figure 4.3 Predicted percent weight loss (PWL) at 3, 6, and 12 months by group and controlling for covariates (N = 363)



CHAPTER 5: LIMITING HIGH VERSUS MAXIMIZING LOW ENERGY DENSE FOODS: A PILOT RANDOMIZED TRIAL COMPARING TWO APPROACHES FOR SIMPLIFIED DIETARY SELF-MONITORING IN A MOBILE WEIGHT LOSS INTERVENTION

Introduction

Over 70% of adults in the United States are living with overweight or obesity (Fryar et al., 2020), which is associated with serious health risks (Calle et al., 2003; Field et al., 2001). Weight loss of 5-10% of initial body weight has been associated with reduced risk for cardiovascular disease (Wing et al., 2011), and behavioral weight loss interventions consistently produce mean weight losses within this range (Alamuddin & Wadden, 2016). Self-monitoring of weight-related behaviors, including weight, physical activity, and diet, is crucial to the success of behavioral weight loss interventions and has been consistently associated with weight loss (Burke et al., 2011a). Self-regulation theory suggests that self-regulation efforts are more successful when individuals self-monitor and compare current behavior with goals, which either bolsters the current behavior or allows for behavioral modification (Kanfer & Karoly, 1972; Bandura, 1991). However, engagement with self-monitoring in weight loss interventions consistently declines over time (Tate et al., 2006; Webber et al., 2008; Power et al., 2019; Tate et al., 2022).

Dietary change is the primary driver of weight loss (Thomas et al., 2014; Thomas et al., 2012), and dietary self-monitoring has been consistently associated with weight loss in behavioral weight loss programs (Baker & Kirschenbaum, 1993; Burke et al., 2011a; Goldstein et al., 2019 Harvey et al., 2019). Burke and colleagues (2011) found that across 15 behavioral weight loss studies that focused on dietary self-monitoring, there were significant associations between self-monitoring and weight loss, and that higher completeness of self-monitoring records was associated with greater weight loss. In a secondary analysis, Goldstein and colleagues (2019) found that adherence to dietary self-monitoring in a behavioral weight loss program was associated with percent weight loss such that more days of self-monitoring corresponded to greater monthly weight losses during that month. In a 24-week behavioral weight control program that was delivered online, Harvey and colleagues (2019) found that frequency and consistency of dietary self-monitoring was significantly related to weight loss. These findings indicate that frequency, consistency, and completeness of dietary self-monitoring contribute to weight loss in behavioral weight loss interventions.

Dietary self-monitoring can be tedious and time-consuming (Burke et al., 2009), and adherence tends to decline over time (Burke et al., 2011a). Digital tools, such as smartphone applications, can reduce the burden of dietary self-monitoring by quickly calculating calories consumed and automatically tracking progress toward a specific calorie goal (Peng et al., 2016). Such tools promote adherence to self-monitoring and enable data collection and delivery of tailored feedback in real-time (Burke et al., 2011b, Burke et al., 2012; Carter et al., 2013; Beasley et al., 2008; Glanz et al., 2006). However, despite the advent of digital tools, engagement with dietary self-monitoring still decreases over time (Power et al., 2019; Goh et al., 2015; Harvey et al., 2019). One possible explanation is that calorie-counting, the traditional approach to dietary monitoring, is too difficult and time-consuming for many participants (Guth, 2018). Calorie counting requires individuals to track all foods eaten and understand the calorie content of those foods; a more simplified approach might only require individuals to monitor a subset of foods, such as foods to avoid (i.e. high-fat/high-sugar) or foods to consume more of (i.e. fruits/vegetables).

Simplified forms of dietary monitoring can reduce participant burden and promote engagement with self-monitoring, which may enhance the effectiveness of behavioral weight loss programs (Epstein et al., 2001; Nezami et al., 2018; Nezami et al., 2022). The Traffic Light Diet (TLD) is a simplified approach to dietary monitoring that categorizes foods into the colors of the stoplight: red, yellow, or green based on their nutrient and energy density (ED), which is the amount of energy in food relative to its weight (kcal/g). Green foods are low-ED, meaning they are high in nutrients and low in calories. This category includes foods such as vegetables, fruits, low-calorie beverages, and diet beverages. Red foods are high-ED, meaning they are higher in calories with low nutrient density. This category includes high-fat and high-sugar foods, such as mayonnaise, ice cream, fried chicken, candy, and cookies. Yellow foods are moderate in calories and include important nutrients for a balanced diet. This category includes most sources of protein, milk and dairy foods, grains, and some fruits and vegetables (Epstein et al., 2001). The TLD has been used in effective weight loss interventions, and previous research has focused on limiting high-ED red foods using the TLD (Epstein et al., 2001; Nezami et al., 2018; Nezami et al., 2022). In a 6-month mobile weight loss intervention that compared traditional calorie monitoring to simplified monitoring of red foods using the TLD, there were no significant differences in weight loss or average daily caloric intake between the two groups (Nezami et al., 2022). Participants who monitored calories lost 5.7% of body weight while participants who monitored red foods lost 4.0% of body weight (Nezami et al., 2022). This evidence suggests that mobile interventions using a simplified dietary approach in which participants monitor only a subset of foods using the TLD can be effective for weight loss.

Targeting consumption of low-ED foods, such as green foods in the TLD, may be an effective dietary strategy to enhance weight loss and improve diet quality compared with limiting high-ED red foods in the TLD. Low-ED diets have been associated with smaller body mass index, lower hunger ratings, lower total energy intake, better diet quality, and weight loss (Vernarelli et al., 2018; Rolls et al., 2005; Ledikwe et al., 2007; Raynor et al., 2012; Ledikwe et al., 2006; Vadiveloo et al., 2018; Ello-Martin et al., 2007). Low-ED diets help lower energy intake without reducing total weight of food eaten, thereby promoting greater satiety than diets that restrict portions (Poppitt & Prentice, 1996). Promoting consumption of low-ED foods instead of restricting high-ED foods may also make it easier to adhere to the dietary goals necessary for weight loss because it focuses on what can be eaten versus what cannot be eaten. Evidence suggests that food choices are motivated by emotional state; foods that are high in fat and sugar have been shown to activate the brain reward pathway, stimulating opioid release and reinforcing consumption of these foods to alleviate stress and improve mood (Adam & Epel, 2007; Gibson, 2006). Restricting consumption of high-ED foods may be a less effective strategy for weight loss than increasing consumption of low-ED foods because it requires behavioral inhibition. Repeatedly inhibiting motivated behaviors, such as eating a desired food in response to emotional distress, can create internal conflict and result in negative psychological and behavioral consequences, including behavioral excess in the form of overeating (Polivy, 1996; Polivy, 1998). Maximizing low-ED green food consumption using the TLD may be a more effective and sustainable dietary approach than restricting high-ED red food consumption because it may simultaneously decrease red food consumption without requiring behavioral inhibition.

A simplified dietary approach that focuses on the subset of foods that can be eaten, such as green foods in the TLD, could be equally if not more effective than a dietary approach that focuses on restricting red foods. However, no weight loss studies have compared the effects of these two simplified dietary approaches using the TLD on engagement with dietary self-monitoring, weight loss, or dietary intake. The present study will compare the feasibility and efficacy of simplified dietary self-monitoring targeting red food reduction to simplified dietary self-monitoring targeting green food promotion on engagement with monitoring, self-reported weight change, and dietary intake at 3 months among overweight or obese young adults. This pilot study is focused on young adults because young adulthood is associated with poor dietary habits and vulnerability to weight gain (Williamson et al., 1990; Adams et al., 2014). The primary outcome was adherence to dietary tracking and goals. Secondary outcomes included weight change (percentage weight loss [PWL] and weight change in kilograms) and change in dietary intake (average daily caloric intake in kcal and Healthy Eating Index [HEI] score) from baseline to 3 months. It was hypothesized that participants in the Green Food monitoring group would have greater adherence to dietary tracking and goals at 3 months and, in turn, greater 3-month weight loss and greater improvements in dietary intake compared with participants in the Red Food monitoring group.

Methods

Study Design

The ADOPT (Alternative Dietary approaches Online to Promote Tracking) study was a parallel-group randomized controlled trial (Clinical Trials ID NCT05049005). The Institutional Review Board at the University of North Carolina at Chapel Hill approved the study.

Participants and Recruitment

Participants were recruited from October 2021 through April 2022 using email lists and advertisements on Facebook and Instagram. Interested individuals completed an online screening survey, and eligible individuals were called by telephone to receive more information about the study. To be eligible, individuals had to be aged 18 to 35 years, have a BMI of 25 to 50 kg/m^2, speak and read English, own a smartphone with an active data plan, and own or purchase a bathroom scale. Exclusion criteria were as follows: (1) have Type I or Type 2 diabetes; (2) current participation in another weight loss or nutrition program; (3) currently taking weight loss medications; (4) being pregnant, breastfeeding, or planning pregnancy in the next 6 months; (5) having preexisting medical conditions for which physician supervision of diet and exercise prescription is needed; (6) having physical problems that limit the ability to exercise; (7) having a history of clinically diagnosed eating disorder; (8) reporting a past diagnosis of or current symptoms of alcohol or substance dependence; (9) having a diagnosis of schizophrenia or bipolar disorder; (10) being hospitalized for a psychiatric diagnosis within the last year; or (11) currently living with another study participant. Individuals who completed the baseline assessment were randomly assigned with equal probability to the Red Food group or the Green Food group. Randomization was stratified based on recent weight loss (10 or more pounds in the last 6 months) and was conducted by a staff member not associated with the study.

Intervention Overview

Elements Common to Both Groups. All participants received an Internet-based dietary intervention with a focus on weight loss based on the Boundary Model for the Regulation of Eating (Herman & Polivy, 1984), Social Cognitive Theory (McAlister et al., 2008; Bandura, 2004), and Self-Regulation Theory (Kanfer & Karoly, 1972). The intervention was delivered remotely via REDCap and included evidence-based behavior change strategies to promote self-monitoring and adherence to personalized goals for dietary intake, including personalized feedback and lessons focused on dietary change, behavioral skills training, and frequent weighing. The only difference between the two groups was the types of foods participants were instructed to self-monitor and the dietary goals participants were given.

Participants first attended a 60-minute virtual group kickoff session, separated by treatment group. During this session, they received their group assignment and login information for the mobile-optimized web-based food log. Participants were recommended to weigh frequently on their scale and report their weight online once per week in REDCap. Participants also received daily dietary goals and tracked their dietary intake, although the target of dietary self-monitoring differed by group. Participants in both groups could view their daily self-monitoring data and progress toward their daily goal in the food log.

Participants also received lessons every week, which they accessed online in REDCap via an email link. Lesson content was tailored for each treatment group and focused on specific areas of diet or eating behavior which participants could focus on changing over the next week. Lessons included behavioral strategies with specific instruction for cognitive and behavioral skills to help participants meet their dietary goals (i.e. self-monitoring, problem solving, planning ahead, stimulus control). Lesson topics included: energy balance, regular weighing, reducing portion sizes, eating out, recipe modification, emotional eating, meal planning, moods and hunger, goal setting, eating in social situations, and more.

Participants also received weekly automated feedback to support their changes, which they accessed online in REDCap via an email link. Computer-tailored algorithms used data from dietary self-monitoring logs over the past week as well as weekly self-reported weight data to generate tailored feedback on weight change and progress toward dietary goals (i.e. feedback on participants' number of days tracking diet, progress toward their dietary goal, and self-reported weight for the week).

Green Food Group

Participants were asked to track only green foods and were given a daily green food goal based on their starting weight and sex (Table 5.1). Green Foods are lower in ED and potentially highly satiating (fruits and vegetables, very lean proteins). The green food goals were created based on average calories in green foods (50 calories/serving), such that increasing consumption would provide for a satiating amount of food and crowd out consumption of higher-calorie red foods, allowing for a weight loss of 0.5 to 1 pound per week. Participants tracked their foods in a mobile-optimized web-based food log, which included four meals (breakfast, lunch, dinner, and snack). Participants were instructed to select the "Skipped" button for any meal in which they consumed zero green foods.

Red Food Group

Participants were asked to track only red foods and were given a daily red food limit based on their starting weight and sex (Table 5.1). Red Foods are higher in ED and may contain less helpful nutrients such as highly processed carbohydrates (white flours and sugar), saturated fats, fats in general, sodium, and meat preservatives. The red food limits were created based on average calories in red foods (225 calories/serving), such that limiting consumption would produce a caloric deficit necessary for a weight loss of 0.5 to 1 pound per week. Participants tracked their foods in a mobile-optimized web-based food log, which included four meals (breakfast, lunch, dinner, and snack). Participants were instructed to select the "Skipped" button for any meal in which they consumed zero red foods.

Measures

Participants completed assessments of weight and dietary intake at baseline and at 3 months and completed online survey measures at baseline and at 3 months. Participants received $25 for completing the 3-month assessment.

Demographics. Standard demographic information was collected via the online survey, including age, race/ethnicity, occupation, education, income, marital status, and weight history.

Adherence to Dietary Tracking and Goals. Adherence to dietary tracking was assessed via frequency of dietary monitoring, or the total number of days during the 3-month intervention that participants tracked breakfast or lunch AND dinner, which was considered a complete (versus partial) day of tracking. Tracking was also considered complete if participants exceeded their red food limit for the day in the Red Food group, or met or exceeded their green food goal for the day in the Green Food group. Each food entry was time-stamped and automatically captured by the web-based food log interface. Adherence to dietary goals was measured as the total number of complete days of tracking during which participants met their dietary goal. Non-adherence was assumed for partial days of tracking, or days where participants did not track.

Weight and Height. Participants self-reported their weight online at baseline and 3 months. Participants were asked to weigh themselves in light clothing without shoes and to have their last meal more than 2 hours prior to weighing. Participants were emailed a link to an online survey where they entered their weight and uploaded a picture of their feet on the scale as a way for study staff to verify that their self-reported weight information was correct. Weight was used to calculate the secondary outcome of percent weight loss (PWL) at 3 months ([(Weight at 3 months − Baseline Weight)/Baseline Weight] × 100). Participants self-reported their height online at baseline via the online survey.

Dietary Intake. Dietary intake was assessed at baseline and 3 months using the Automated Self-Administered 24-Hour Recall (ASA24). This system guides participants through a multi-pass recall of foods eaten over the previous 24 hours. Intake was measured twice (one weekday and one weekend day) at each time point to provide the most accurate representation of typical consumption. The recalls were unscheduled, and participants had to check their email for notifications that their recall was ready to be completed. This information was used to calculate average daily caloric intake in kilocalories per day. The Healthy Eating Index score (HEI)-2015 was also calculated to assess diet quality based on the major dietary recommendations of the 2015 Dietary Guidelines for Americans (DGA). The HEI score ranges from 0 to 100, with higher scores indicating closer compliance with the 2015 DGA.

Program Acceptability and Satisfaction

Participants answered questions about program satisfaction and perceptions of self-monitoring via the online survey at 3 months.

Statistical Analyses

Analyses were conducted using SAS software version 9.4. Descriptive statistics were calculated for baseline demographic characteristics. Analyses examining baseline characteristics as confounders were conducted, however, none were significantly associated with both treatment group and outcomes. A between-groups t-test was used to examine differences in complete dietary tracking days and days the dietary goals were met between groups. Pearson correlations were used to determine the correlation between complete dietary tracking days and days the dietary goals were met and PWL within each treatment group. Paired t-tests were used to evaluate within-group change over time in weight (kilograms), average daily caloric intake, and

HEI score. Linear regression was used to evaluate the effect of treatment group on PWL, weight change (kilograms), average daily caloric intake, and HEI score at 3 months. Models for weight change (kilograms), average daily caloric intake, and HEI score included the 3-month value as the dependent variable, with a covariate for the baseline value. Sensitivity analyses were conducted with baseline values carried forward for missing data. Finally, χ^2 tests evaluated differences between groups in the percentage of participants who lost 3% and 5% of their body weight.

Results

Of the 60 enrolled and randomized participants, 34 were assigned to the Green Food group and 26 to the Red Food group (Figure 5.1). Participants were, on average (mean [SD]), 29.1 (4.3) years old with a BMI of 33.2 (6.3) kg/m^2. Baseline demographics of participants by treatment group are presented in Table 5.2. There were no significant differences between groups. Given that adherence to dietary tracking and adherence to dietary goals were captured automatically by the web-based food log interface, retention on the primary outcome was 100% at 3 months. Retention on the secondary outcome of weight change was 82% at 3 months, while retention on the secondary outcome of change in dietary intake was 63% at 3 months. Five participants who did not complete the final weight measurement were in the Green Food group, compared with n = 6 in the Red Food group (Fisher's Exact Test, p = .51). Thirteen participants who did not complete the final dietary assessment were in the Green Food group, compared with n = 9 in the Red Food group (Fisher's Exact Test, p = .79). T-tests revealed that baseline BMI did not differ between those who completed the final weight measurement (n = 49) and those who did not (n = 11; 33.5 [SD=6.2] vs. 32.0 [SD = 6.9], p = .48), nor between those who completed the final dietary assessment (n = 38) and those who did not (n = 22; 33.69 [SD = 6.5] vs. 32.33 [SD = 6.0], p = .43).

Self-Monitoring Engagement

Results of the primary outcome analyses are in Table 5.3. There were no between-group differences in complete dietary tracking days or days the dietary goal was met over 3 months. Green Food group participants had an average of 32.4 complete dietary tracking days (95% CI: 23.7-41.1; median = 35, interquartile range = 8-52) compared with 30.9 days (95% CI: 21.3-40.5; median = 32, interquartile range = 3-50) among Red Food group participants. Green Food group participants had an average of 19.2 days the dietary goal was met (95% CI: 12.0-26.4; median = 15, interquartile range = 3-32) compared with 20.1 days (95% CI: 12.3-27.8; median = 16, interquartile range = 2-35) among Red Food group participants. There were no significant correlations between PWL and complete dietary tracking days or days the dietary goal was met in either group. Figure 5.2 displays the percent of participants who were still self-monitoring diet in each month of the study by treatment group, in addition to the average percentage of days tracked each month by treatment group.

Weight Change

Results of the secondary outcome analyses are in Table 5.4. For the secondary outcome of weight change among completers (N = 49), PWL at 3 months was −0.33% (95% CI: -1.28% to 0.63%) in the Green Food group and −1.96% (95% CI: −3.64% to −0.27%) in the Red Food group. Linear regression revealed that there were no between-group differences in change over time ($p = .07$). Paired t-tests revealed that within-group change for PWL from baseline to 3 months was significant for the Red Food group ($p = .02$), but not for the Green Food group ($p = .41$). A sensitivity analysis with the baseline value for weight carried forward to account for missing data revealed similar results. Among completers, Green Food group participants lost 0.3 kg at 3 months (SD = 2.41; 95% CI: −1.21 to 0.62), and Red Food group participants lost 1.57 kg (SD = 3.34; 95% CI: −3.13 to −0.01). Linear regression revealed that there were no between-group differences in change over time (p = .13). Paired t-tests revealed that within-group change in weight (kg) from baseline to 3 months was significant for the Red Food group (p = .05), but not for the Green Food group (p = .52, 95% CIs = -2.26 to -0.15). A sensitivity analysis with the baseline value for weight carried forward to account for missing data revealed similar results.

Change in Dietary Intake

For the secondary outcome of change in dietary intake among completers (N = 38), Green Food group participants reduced average daily caloric intake by 155.40 kcal (SD = 610.73; 95% CI: -433.40 to 122.60), while Red Food group participants reduced average daily caloric intake by 335.83 kcal at 3 months (SD = 1057.17; 95% CI: -879.38 to 207.72). Linear regression revealed that there were no between-group differences in change over time (p = .51) and paired t-tests revealed that within-group change from baseline to 3 months was not significant for either group. A sensitivity analysis with the baseline value for dietary intake carried forward to account for missing data revealed similar results. Among completers, HEI score increased by 7.84 units for participants in the Green Food group (SD = 15.07; 95% CI: 0.98 to 14.70), compared with an increase of 6.81 units for participants in the Red Food group (SD = 10.49; 95% CI: 1.42 to 12.20). Linear regression revealed that there were no between-group differences in change over time (p = .81). Paired t-tests revealed that within-group change for HEI score from baseline to 3 months was significant for both the Green Food (p = .03) and Red Food groups (p = .02). A sensitivity analysis with the baseline value for HEI score carried forward to account for missing data revealed similar results.

Three and Five Percent Weight Loss

There were significant between-group differences in the percentage of participants who reached 5% weight loss at 3 months. Among all randomized participants (with baseline weight used for missing weight observations), 23.1% in the Red Food group (n = 6) and 0% in the

Green Food group (n = 0) lost 5% ($\chi2 = 8.72$, $p = .005$). There were no between-group differences in the percentage of participants who reached 3% weight loss at 3 months. Among all randomized participants, 26.9% in the Red Food group (n = 7) and 20.6% in the Green Food group (n = 7) lost 3% ($\chi2 = 0.33$, $p = .76$). Among completers in the Red Food group (n = 20), 30% lost 5% and 35% lost 3%. Among completers in the Green Food group (n = 29), 24.1% lost 3%.

Program Evaluation

There were no significant differences in program evaluation scores between the two groups. Out of the 47 participants who completed the online questionnaires at 3 months, the percentage of participants who responded they would "probably" or "definitely" recommend the program to others was similar between groups (74% in Green Food group and 80% in Red Food group; Table 5.5). No participants responded they would "definitely not" recommend the program to others.

Discussion

The objective of this study was to compare the feasibility and efficacy of two simplified dietary self-monitoring approaches using the TLD on engagement, self-reported weight change, and dietary intake at 3 months among overweight or obese young adults. There were no between-group differences in adherence to complete days of dietary tracking or adherence to dietary goals over 3 months. Among completers, participants in the Red Food group lost 1.57 kg and −1.96% of body weight at 3 months, while participants in the Green Food group did not lose weight (-0.3 kg and −0.33% of body weight). Change over time for PWL and weight in kg was only significant for the Red Food group. Additionally, 23.1% of participants in the Red Food group achieved 5% weight loss, compared with none in the Green Food group. Among completers, participants in the Red Food group decreased calorie intake by 335.83 kcal and increased HEI score by 6.81 units, while participants in the Green Food group decreased calorie intake by 155.40 kcal and increased HEI score by 7.84 units at 3 months. Change over time was not significant for average daily caloric intake but was significant for HEI score in both groups. These findings suggest that while simplified dietary self-monitoring targeting green food promotion may improve diet quality, limiting red foods appears to be a more effective simplified dietary self-monitoring strategy for weight loss.

The first hypothesis of this study was that participants in the Green Food group would have greater adherence to dietary tracking and dietary goals at 3 months compared with participants in the Red Food group. However, this study found no between-group differences in the number of complete tracking days or the number of days the dietary goal was met over time. Engagement with tracking similarly declined over time in both groups. Monitoring green foods may have been inherently more burdensome than monitoring red foods given that the green food goals were higher than the red food limits, requiring participants to monitor a greater number of foods. In a conceptual framework for engagement with digital behavior change interventions, Perski and colleagues (2017) propose that engagement is influenced by three factors: 1) the intervention itself (i.e. content and mode of delivery); 2) the context (i.e. setting and population), and; 3) the target behavior. It is possible that the mode of delivery (i.e. the mobile-optimized web-based food log) mitigated engagement in the current intervention. The mobile-optimized web-based food log developed for this study lacked convenient features that are included in other commercially available dietary tracking apps, such as MyFitnessPal™ or Fitbit™. For example, instead of manually searching for each food item, commercial apps often include options for "frequent" and "recent" foods, as well as a bar code scanner for packaged food items. Additionally, the user experience of the food log used in this study was less refined than that of commercial apps. For example, participants in this study reported difficulty using the search bar to find food items and editing logged food choices in the food log. Finally, the food list in the food log included a limited number of foods and lacked variety for certain food groups, such as meat alternatives. It is possible that the limited functionality of the food log diminished overall levels of engagement in the current intervention rather than the specific dietary approach that participants were assigned. This effect would have been identical across groups since both groups used the same food log. Future studies could explore whether improved user experience and increased functionality of the food log enhances engagement with simplified dietary self-monitoring using the TLD.

The second hypothesis of this study was that participants in the Green Food group would have greater 3-month weight loss compared with participants in the Red Food group. However, a significantly greater proportion of participants in the Red Food group achieved 5% weight loss at 3 months compared with the Green Food group. Although nonsignificant, the effect of treatment group on PWL over time was trending ($p = .07$), and it is possible that a treatment effect could have been detected if this study had more power. Additionally, within-group change for PWL and weight change in kg was significant for the Red Food group but not for the Green Food group. Participants in the Red Food group lost 1.57 kg on average at 3 months, which is similar to another study that utilized red food monitoring among mothers with young children, where average weight loss was 2.4 kg at 6 months (Nezami et al., 2018). In another study that compared traditional calorie monitoring to simplified red food monitoring, Nezami and colleagues (2022) found that participants monitoring red foods lost 3.5 kg on average at 6 months, which would likely be slightly higher than the current study given the average 3-month weight loss of 1.57 kg. However, this discrepancy may be explained by the fact that Nezami and colleagues (2022) included personalized goals for physical activity, while the current study did not. These findings suggest that the more restrictive approach of limiting red food intake may be more effective for weight loss than the less restrictive approach of maximizing green food intake.

It is possible that participants in the Red Food group experienced greater increases in dietary restraint than participants in the Green Food group, which may have resulted in a greater proportion of Red Food group participants achieving 5% weight loss at 3 months. Dietary restraint is the conscious restriction of food intake to control weight and has been associated with lower overall food intake, weight loss, and successful weight loss maintenance (De Castro, 1996; Lowe & Kleifield, 1988; McGuire et al., 2001). Evidence suggests that dietary restraint is a multidimensional construct, consisting of two subscales: flexible and rigid restraint (Westenhoefer et al., 1991). Flexible restraint has been associated with lower BMI, while rigid restraint has been associated with higher BMI (Westenhoefer et al., 1999). Bacon and colleagues (2002) conducted a 1-year randomized controlled trial comparing a traditional "weight loss-centered" diet program to an alternative "health-centered" non-diet wellness program. They found that participants in the diet program lost a significant amount of weight and increased on measures of flexible restraint, while participants in the non-diet program did not lose weight and had no change on measures of flexible restraint (Bacon et al., 2002). Given the more restrictive nature of the red food limiting approach in the current study, it is possible that participants in the Red Food group increased on measures of flexible restraint while participants in the Green Food group did not, which may have been one mechanism for weight loss. Future research could explore whether flexible restraint mediated weight change for participants across groups.

Finally, it was hypothesized that participants in the Green Food group would have greater improvements in dietary intake at 3 months compared with participants in the Red Food group.

However, there was no effect of treatment group on change in average daily caloric intake or change in HEI score over time. HEI score increased significantly over time in both groups, suggesting that both the red food limiting and green food maximizing approaches positively impact diet quality, but only the red food limiting approach impacts weight. Evidence suggests that a combined dietary approach could be more effective for weight loss (Vadiveloo et al., 2018; Ello-Martin et al., 2007). In a secondary analysis of dietary data from participants in an 18-month randomized controlled weight loss intervention, Vadiveloo and colleagues (2018) found that individuals who consumed both a high number of low-ED foods (≥6.6 per day) and a low number of high-ED foods (≤2 per day) experienced greater reductions in BMI and percent weight loss at 6 and 18 months than individuals who only met the high-ED target. Ello-Martin and colleagues (2007) conducted a clinical trial to test the effectiveness of two strategies to reduce dietary ED on body weight over 12 months; one group was told to reduce fat intake while the other group was told to reduce fat intake and increase fruit/vegetable intake. Both groups significantly reduced dietary ED, however, the reduce fat and increase fruit/vegetable group lost significantly more weight at 6 and 12 months compared with the reduce fat group. These results demonstrate that a dietary approach that targets consumption of low-ED foods in conjunction with limiting high-ED foods contributes to weight loss in the context of a weight loss intervention. Future studies could compare simplified dietary self-monitoring targeting red food reduction to simplified dietary self-monitoring targeting both red food reduction and green food promotion using the TLD to explore differential impacts on weight and dietary intake. Given that a combined dietary approach would require monitoring more foods than red food limiting alone, future research could also explore whether engagement outcomes differ between these two approaches.

In conclusion, this pilot study contributes to the growing body of evidence that simplified dietary self-monitoring of high-calorie red foods in the TLD is effective for both weight loss and improving diet quality in the context of a dietary intervention with a focus on weight loss. This study has several strengths and weaknesses. One strength is that the current study included elements that are considered integral for behavior change, including self-monitoring, goal setting, and personalized feedback. The feedback messages were written in advance and delivered automatically, therefore, they were standardized across participants and delivered with high fidelity. Additionally, the average 3-month weight loss of 1.57 kg observed among completers in the Red Food group was similar to that reported in a meta-analysis of 11 mobile phone app interventions, which found weight loss of 1.07 kg when compared with control groups (Islam et al., 2020). Weaknesses of this study include a small sample size and high levels of attrition. This study was delivered entirely remotely due to impacts from the COVID-19 pandemic and was largely automated. There was only one contact with study staff via the virtual group kickoff session, and the lack of person-to-person contact during the intervention period may have yielded high attrition (18%) at 3-months. Because the intervention was delivered remotely, it is also possible that participants were using other dietary tracking apps during the intervention, which could have confounded the association between simplified dietary self-monitoring and change in weight or dietary intake in this study. Another weakness of the current study is that the secondary outcome of weight was self-reported, which could have resulted in measurement bias. However, participants were required to upload a picture of their feet on the scale at baseline and at 3 months, and study staff verified that the self-reported weight information matched the picture. Finally, participants in this study were predominately highly educated white women, which limits the generalizability of these findings. Future research could explore the impact of user experience on engagement with technology-based dietary monitoring, psychosocial mediators between diet and weight loss, as well as a dietary approach combining red and green food monitoring using the TLD.

Table 5.1 Dietary goals based on starting weight and sex

Starting weight (lbs)	**Red Food Limit**		**Green Food Goal**	
	Women	Men	Women	Men
150-174	3	3	6	7
175-199	3	4	6	8
200-224	4	4	6	8
225-249	4	5	7	8
250-274	4	5	8	9
275-299	4	6	9	9
300-324	5	7	9	10
≥325	5	7	10	11

Table 5.2 Baseline characteristics by treatment group

	Green Food Group (N=34)	**Red Food Group (N=26)**
Age (y), mean ± SD	28.6 ± 4.2	29.6 ± 4.5
Female	26 (76.5)	25 (96.2)
Ethnicity		
Hispanic/Latino	3 (8.8)	2 (7.7)
Non-Hispanic/Latino	31 (91.2)	24 (92.3)
Race		
American Indian or Alaska Native	1 (2.9)	0
Asian	4 (11.8)	3 (11.5)
Black or African American	11 (32.4)	9 (34.6)
White	19 (55.9)	14 (53.9)
Other[a]	1 (2.9)	0
Education		
High school, vocational training, or some college	1 (2.9)	4 (15.4)
Bachelor's degree	21 (61.8)	10 (38.5)
Graduate or professional degree	12 (35.3)	12 (46.2)
Marital status		
Married or living with partner	19 (55.9)	16 (61.6)
Not married or living with partner	15 (44.1)	10 (38.5)
Lost 10 pounds in last 6 months	4 (11.8)	3 (11.5)
Weight (kg), mean ± SD	91.9 ± 19.5	92.4 ± 20.8
BMI (kg/m^2), mean ± SD	32.1 ± 5.7	34.6 ± 6.8

Note: All data given as n (%) unless otherwise indicated.
[a]Other = checked the response option "Other" and race is unknown.

Table 5.3 Mean and median complete dietary tracking days and days goal was met between groups

	Mean (95% CI)	Median (IQR)	*p* value[a]
Number of Complete Tracking Days			
Green Food Group (N=34)	32.4 (23.7, 41.1)	35 (8, 52)	.81
Red Food Group (N=26)	30.9 (21.3, 40.5)	32 (3, 50)	
Number of Days Goal Met			
Green Food Group (N=34)	19.2 (12.0, 26.4)	15 (3, 32)	.87
Red Food Group (N=26)	20.1 (12.3, 27.8)	16 (2, 35)	

[a]Between group t-test for difference in complete tracking days and days goal met between treatment groups.

Table 5.4 Weight change and change in dietary intake within and between groups among completers

Variable	**Baseline Mean (95% CI)**	**Mean change from baseline to 3 months Mean (95% CI)**	***p* value[a]**
Percent weight change			
Green Food Group (N=29)	-	-0.33 (-1.28 to 0.63)	0.07
Red Food Group (N=20)	-	-1.96 (-3.64 to -0.27)*	
Weight (kg)			
Green Food Group (N=29)	91.9 (85.1, 98.7)	-0.30 (-1.21 to 0.62)	0.13
Red Food Group (N=20)	92.4 (84.0, 100.9)	-1.57 (-3.13 to -0.01)*	
Average daily caloric intake (kcal/day)			
Green Food Group (N=21)	2227.6 (1991.8, 2463.3)	-155.40 (-433.40 to 122.60)	
Red Food Group (N=17)	2004.9 (1703.6, 2306.2)	-335.83 (-879.38 to 207.72)	0.51
HEI score			
Green Food Group (N=21)	49.2 (45.4, 52.9)	7.84 (0.98 to 14.70)*	0.81
Red Food Group (N=17)	49.4 (43.9, 54.9)	6.81 (1.42 to 12.20)*	

[a]Linear regression with treatment as independent variable, models for weight (kg), average daily caloric intake (kcal/day), and HEI score include covariate for baseline levels.
*Significant at $p \leq .05$ level for within-group change over time (paired t-test).

Table 5.5 Program evaluation and perceptions of dietary self-monitoring by treatment group among completers

Variable	Responses	Green Food Group (n=27) Mean (SD)/% (n)	Red Food Group (n=20) Mean (SD)/% (n)
How difficult was it to make the prescribed changes in your diet over the last 3 months?	Likert scale 1=Very easy to 8=Very difficult	5.2 (1.5)	5.3 (1.3)
How satisfied are you with what you've achieved in this program?	Likert scale 1=Not satisfied to 8=Very satisfied	3.9 (2.5)	4.8 (2.5)
How confident are you that you will continue to follow the approach to eating you were taught during this program?	Likert scale 1=Not confident to 8=Very confident	4.9 (2.1)	4.9 (1.8)
How difficult was it to track your eating behaviors over the last 3 months?	Likert scale 1=Very easy to 8=Very difficult	4.9 (2.3)	4.9 (1.8)
How helpful was the Traffic Light Log for you in pursuing your weight loss goal?[a]	Likert scale 1=Not at all helpful to 8=Very helpful	5.1 (2.1)	5.4 (2.1)
How easy was it to learn how to use the Traffic Light Log?	Likert scale 1=Very easy to 8=Very difficult	3.4 (2.4)	3.6 (2.3)
How likely are you to continue to use the food tracking approach to make dietary changes after the program?	Likert scale 1=Very unlikely to 8=Very likely	4.6 (2.4)	4.5 (1.9)
Would you recommend the program you received from ADOPT to others?	Definitely not Probably not Probably would Definitely would	0.0 (0) 25.9 (7) 40.7 (11) 33.3 (9)	0.0 (0) 20.0 (4) 45.0 (9) 35.0 (7)

[a]n=19 for Red Food group
*Between-group difference significant at p value < 0.05 (t-test or Mantel–Haenszel chi-square test).

Figure 5.1 Study recruitment, enrollment, and retention (CONSORT). CONSORT, Consolidated Standards of Reporting Trials

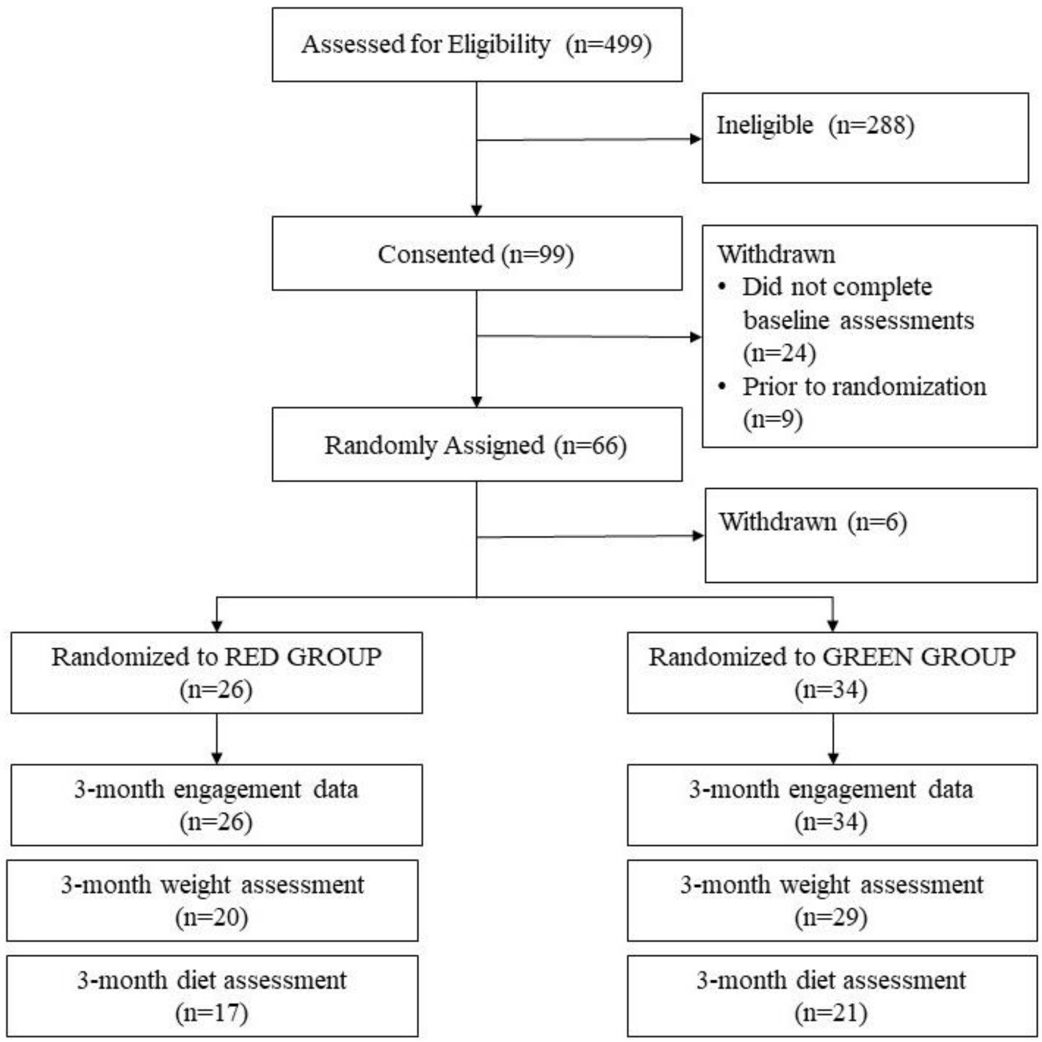
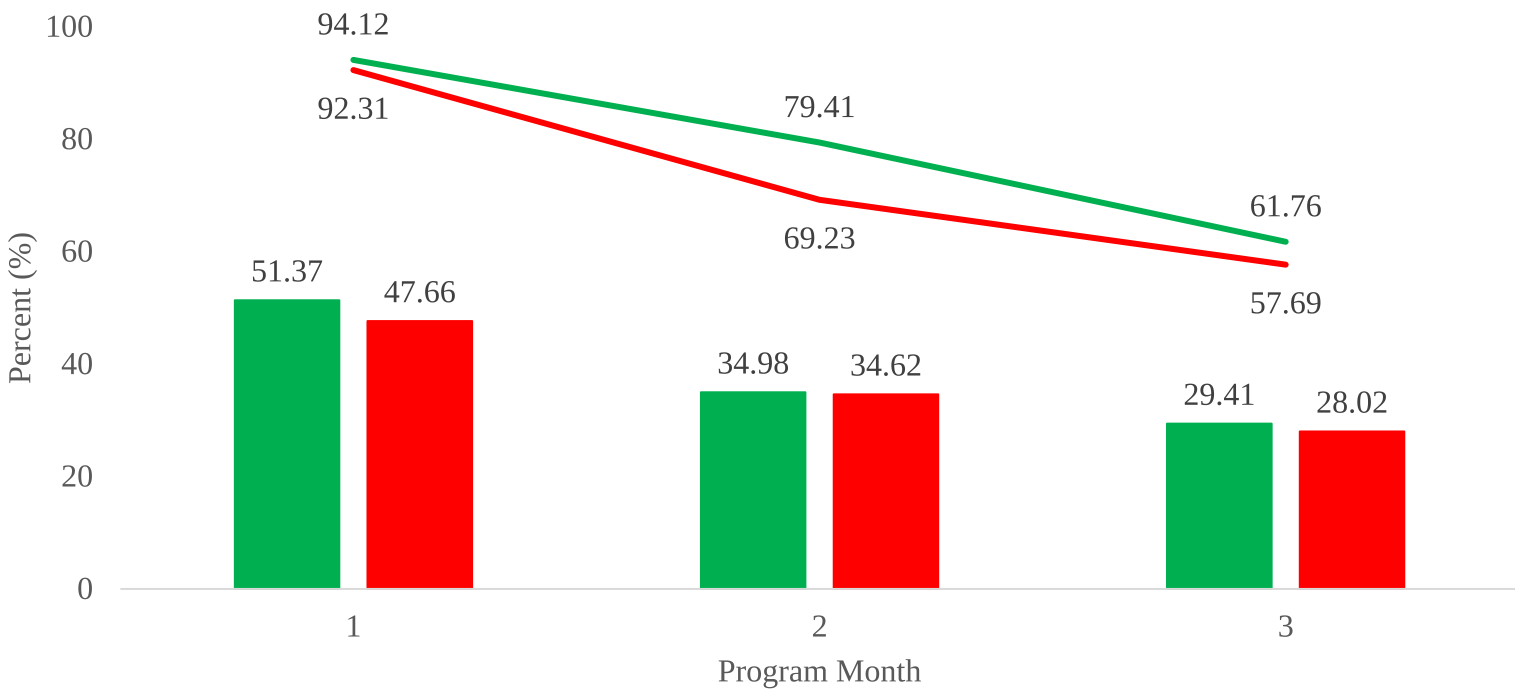


Figure 5.2 Adherence to self-monitoring by treatment group across each program month[a]



[a]Bars represent the average percent of days of complete dietary tracking among participants and lines represent the percent of participants who tracked at least one complete day that month.

CHAPTER 6: SYNTHESIS

Summary of Findings

Obesity has reached epidemic proportions in the United States. Digital weight loss interventions are effective for weight loss, and engagement in digital weight loss interventions, especially with self-monitoring of weight-related behaviors, is crucial for success. Given that engagement with self-monitoring consistently declines over time across digital weight loss interventions, understanding effective trajectory patterns of engagement with self-monitoring, as well as whether and to what extent novel approaches for simplified self-monitoring enhance intervention engagement, could improve the efficacy of digital weight loss programs. The purpose of these studies was to (1) examine multivariate trajectories of engagement over 12 months in an effective online weight loss intervention to identify meaningful groups of individuals based on their individual patterns of engagement with self-monitoring; and (2) compare the feasibility and efficacy of two simplified dietary self-monitoring approaches using the Traffic Light Diet (TLD) on engagement, self-reported weight change, and dietary intake at 3 months among overweight or obese young adults. The primary findings of this dissertation were that (1) Four engagement patterns for self-monitoring emerged (never-engagers, low/declining engagers, early engagers, and sustained-engagers), and predicted percent weight loss was clinically significant at 12 months for both sustained-engagers and early engagers, but not for low/declining or never-engagers; and (2) there were no differences in engagement with dietary tracking or adherence to dietary goals between the Red and Green Food groups at 3 months, however, the more restrictive approach of limiting red food intake appears to be more effective for weight loss than the less restrictive approach of maximizing green food intake. Overall, the results of this dissertation suggest that individual engagement patterns are similar across self-monitoring behaviors and can predict treatment response; and that while a simplified dietary approach targeting red food reduction can enhance weight loss and diet quality, engagement with self-monitoring may depend upon other factors, such as the usability and design of the self-monitoring tool rather than the specific dietary approach.

One of the most consistent findings related to engagement in digital weight loss interventions is that engagement declines over time (Tate et al., 2006; Webber et al., 2008; Turner-McGrievy & Tate, 2013; Power et al., 2019). Although engagement declines over time, more research is needed to determine whether this pattern is detrimental for weight loss, especially if it occurs later in the program. For example, participants may have already lost weight during the first half of the intervention and are maintaining weight loss during the second half of the intervention. Therefore, it is possible that the same level of engagement would not be necessary in the second versus the first half of the intervention. Thus, patterns of engagement may vary across participants (Power et al., 2019; Demment et al., 2014; Goh et al., 2015), and previous research has detected qualitatively distinct patterns of engagement in digital weight loss interventions based on basic site usage data such as logins, page views, average time spent on a page, and more (Power et al., 2019; Glasgow et al., 2011). The variable-centered approaches used in these studies are ideal for describing relationships among variables but are less focused on identifying individual response patterns. Grouping individuals based on individual response patterns is a useful approach for understanding how individual use of an intervention is associated with outcomes and could shed light on which usage patterns are most beneficial.

Study One used latent class growth modeling with another mixture layer to identify groups of participants based on trajectories of engagement with self-monitoring of weight, diet, and physical activity among overweight or obese adults participating in an effective 12-month digital weight loss intervention. This study identified four engagement patterns: never-engagers, low/declining engagers, early engagers, and sustained-engagers. Predicted percent weight loss was clinically significant at 12 months for both sustained-engagers (10.4%) and early engagers (5.1%), but not for low/declining (1.3%) or never-engagers (0.48%). Low/declining engagers comprised 48.5% of the sample and did not achieve 5% weight loss at 12 months. Given the high proportion of low/declining engagers and given that these participants did not achieve the intended weight loss outcomes of the intervention, there is a need to characterize and identify these participants early on to promote sustained engagement with self-monitoring, especially after 6 months.

This study found that relative to the low/declining engager class, participants with a higher BMI were significantly less likely to be in the early-engager class, and older participants were significantly more likely to be in the sustained-engager class. These findings suggest that younger participants with a higher BMI may be more prone to low/declining engagement and may need more support to sustain engagement with self-monitoring in digital weight loss interventions. Future research could examine a wider range of predictors, including psychosocial constructs, such as baseline motivation and self-efficacy, to further characterize individuals at risk of low/declining engagement. Adaptive interventions could then provide additional support to these individuals, such as meetings with a health coach or motivational interviewing, once a lapse in self-monitoring occurs.

Given the high proportion of participants categorized as low/declining engagers in Study One, it is important to understand ways to promote greater engagement in digital weight loss interventions, which could improve the efficacy of such programs. Digital tools, such as smartphone applications, smart scales, and wearable devices can reduce the burden of self-monitoring by automatically capturing weight and activity data, and quickly calculating calories consumed and tracking progress toward a calorie goal (Peng et al., 2016). However, although technology can promote adherence to self-monitoring (Burke et al., 2012; Carter et al., 2013), engagement with dietary self-monitoring still declines over time (Power et al., 2019; Goh et al., 2015; Harvey et al., 2019). One possible explanation is that calorie-counting, the traditional approach to dietary monitoring, is too difficult and time-consuming for many participants (Guth, 2018). Simplified forms of dietary monitoring can reduce participant burden and promote engagement with self-monitoring, which may enhance the effectiveness of behavioral weight loss programs (Epstein et al., 2001; Nezami et al., 2018; Nezami et al., 2022).

Study Two compared the feasibility and efficacy of simplified dietary self-monitoring targeting red food reduction (Red Food group) to simplified dietary self-monitoring targeting green food promotion (Green Food group) using the TLD on engagement, self-reported weight change, and dietary intake at 3 months among overweight or obese young adults. A total of 499 young adult men and women were interested in the study, but after removing ineligible participants and those who did not complete baseline questionnaires, 66 young adults were randomized to either the Red Food or Green Food group. Two participants withdrew for medical reasons and four withdrew because they were no longer interested, leaving a total of 60 randomized participants. The intervention was delivered entirely remotely through REDCap, a mobile-optimized website, and e-mails, with only one face-to-face kickoff session that was conducted via Zoom. The intervention was based on the Boundary Model for the Regulation of Eating (Herman & Polivy, 1984), Social Cognitive Theory (McAlister et al., 2008; Bandura, 2004), and Self-Regulation Theory (Kanfer & Karoly, 1972). The primary outcome was engagement with dietary tracking and adherence to dietary goals at 3 months, and secondary outcomes included change in weight and dietary intake from baseline to 3 months. It was hypothesized that participants in the Green Food group would have greater adherence to dietary tracking and goals at 3 months and, in turn, greater 3-month weight loss and greater improvements in dietary intake compared with participants in the Red Food group.

The ADOPT intervention did not produce any between-group differences in engagement with dietary tracking or adherence to dietary goals at 3 months. Nezami and colleagues (2022) also found no difference in dietary tracking days over 6 months between the Standard calorie-monitoring group and the Simplified red food-monitoring group. Additionally, number of complete dietary tracking days and number of days the dietary goal was met were not significantly correlated with PWL in either group, which is consistent with Nezami and colleagues (2022) finding that dietary tracking days was not significantly correlated with PWL for the Simplified red food-monitoring group. These findings suggest that specific dietary approach may not impact engagement with dietary tracking or adherence to dietary goals. There are several theories related to the adoption and use of technology in the mobile health literature. The Technology Acceptance Model (Davis, 1989) suggests that one's attitude toward using technology (which influences behavioral intention and actual use of the technology) is determined by perceived usefulness and perceived ease of use of the technology. In this model, perceived ease of use also influences perceived usefulness. Although the dietary approaches tested in Study Two were simplified (i.e. required monitoring only a subset of foods rather than all foods), it is possible that participants in this study did not perceive the mobile-optimized web-based food log as easy to use, which may have impacted perceived usefulness of this tool and attitudes/intentions toward self-monitoring diet. Vaghefi and Tulu (2019) propose two dimensions that are related to the continued use of mHealth apps: user experience (i.e. extent to which technology enables users to achieve their intended goals) and user's intent (i.e. level of commitment to their health goals). In this model, user experience is influenced by a number of factors, including the interface design (i.e. screen display) and navigation (i.e. how users move through the menus and different features to accomplish tasks). The user experience of the food log used in this study was less refined than that of many commercial dietary tracking apps. For example, participants in this study reported difficulty using the search bar to find food items and editing logged food choices in the food log. Participants also reported frustration that some of the foods they commonly ate were not listed in the food log and had to be logged as "miscellaneous foods." Therefore, it is possible that perceived ease of use of the food log was low and that the overall user experience attenuated engagement with dietary self-monitoring rather than the specific dietary approach that participants were assigned.

It is also possible that the food log was not simplified enough, which may have contributed to participants' overall user experience. The food log was designed to remove specificity from dietary self-monitoring and allow for selection of very general food categories. In the ADOPT intervention, participants were required to search for specific food items that were categorized as red or green. However, participants may perceive the food log as easier to use if they were only allowed to log a "red food" or a "green food", rather than having to select specific foods within each category. Future research could test whether further simplifying these dietary self-monitoring approaches improves engagement with monitoring.

Study Two found a significant difference between groups in the proportion of participants who achieved clinically significant weight loss at 3 months, such that 23.1% of participants in the Red Food group achieved 5% weight loss compared with none in the Green Food group. These findings suggest that limiting red foods may be a more effective simplified dietary approach for weight loss. There are many mechanisms through which the dietary approach of limiting red foods could have resulted in a higher proportion of participants achieving 5% weight loss. Given that the red food limiting approach required dietary restriction and the green food maximizing approach did not, it is possible that participants in the Red Food group experienced greater increases in dietary restraint, specifically flexible restraint, than participants in the Green Food group. In a 1-year randomized controlled trial, Bacon and colleagues (2002) compared a traditional "weight loss-centered" diet program to a "health-centered" non-diet wellness program and found that participants in the diet program lost a significant amount of weight and increased on measures of flexible restraint, while participants in the non-diet program did not. Therefore, it is possible that dietary restriction is necessary for weight loss. Thus, it is possible that participants in the Green Food group did not limit any red foods or replace any red foods with green foods as would be necessary to lower calorie intake and to produce weight loss.

Self-efficacy may be another important mechanism for change in dietary behaviors (Shaikh et al., 2008). Some studies have shown that self-efficacy increases over the course of weight loss treatment (Clark et al., 1991; Pinto et al., 1999) and predicts subsequent weight loss (Edell et al., 1987; Jeffery et al., 1984). However, more research is needed to determine how different dietary approaches for weight loss impact self-efficacy beliefs. It is possible that participants in the Green Food group faced more barriers to making the dietary changes necessary to meet their daily dietary goal, and thereby experienced greater decreases in self-efficacy beliefs for dietary change, compared with participants in the Red Food group. Taste preferences, higher costs associated with healthy eating, limited availability of healthy foods, and the time commitment needed to cook/prepare healthy foods are some of the barriers that participants in the Green Food group may have faced when trying to adhere to a daily green food goal. The dietary changes required to limit red food intake and meet a red food limit may be less burdensome than the dietary changes required to increase green food intake and reach a green food goal, thereby differentially impacting self-efficacy beliefs between groups. Future research could explore these potential mediators between dietary approach and weight loss.

Change in diet quality over time was also significant for both groups such that total Healthy Eating Index (HEI) score increased by 6.81 and 7.84 units for participants in the Red Food and Green Food groups, respectively. Change over time was not significantly different between groups. The HEI-2015 contains 13 components that sum to a total maximum score of 100 points, including adequacy components, or foods to eat more of for good health (i.e. total fruits/vegetables, whole grains, dairy, total protein foods, etc.); and moderation components, or foods to limit for good health (i.e. refined grains, sodium, added sugars, and saturated fats). This study did not examine change in the individual components that comprise the total HEI score. It is possible that participants in the Red Food group experienced changes in moderation components (i.e. limiting foods high in added sugars and saturated fats), while participants in the Green Food group experienced changes in adequacy components (i.e. maximizing total fruits/vegetables and lean proteins), which both would result in improved total HEI score. Evidence suggests that increasing consumption of low-ED foods, such as green foods in the TLD, can simultaneously decrease fat intake (Epstein et al., 2001). However, it is unclear whether and to what extent decreasing fat intake can simultaneously increase consumption of low-ED foods. Future research could examine change over time in the 13 components that comprise total HEI score to better understand whether improvements in diet quality occurred via different mechanisms between the Red Food and Green Food groups.

The results of this dissertation suggest that individual engagement patterns are similar across self-monitoring behaviors, can predict treatment response, and that the large proportion of participants who exhibit the low/declining engagement pattern may need additional support to sustain engagement with self-monitoring after 6 months. Additionally, while a simplified dietary approach targeting red food reduction can enhance weight loss and diet quality compared with a simplified dietary approach targeting green food promotion, engagement with self-monitoring may depend upon other factors, such as the usability and design of the self-monitoring tool. Perceived ease of use and overall user experience are likely important factors to consider when examining engagement with dietary self-monitoring in digital weight loss interventions. Strengths of this dissertation include using a powerful data-driven analysis that identified true usage patterns based on multiple trajectories of engagement with self-monitoring over 12 months. Additionally, the ADOPT intervention was delivered entirely remotely due to impacts from the COVID-19 pandemic and the average 3-month weight loss of 1.57 kg observed among completers in the Red Food group was similar to the 1.07 kg reported in a meta-analysis of 11 mobile phone app interventions (Islam et al., 2020), but slightly lower than a prior weight loss intervention using the red food monitoring approach (Nezami et al., 2022). Future research avenues include examining predictors of low/declining engagement, analyzing mediators between dietary approach and weight change, and exploring how to optimize the user experience of online tools developed for digital weight loss interventions.

Implications for Research and Future Directions

The results of this dissertation contribute to the development and dissemination of digital weight loss interventions in several ways. First, it demonstrates that a large proportion of participants exhibit low/declining engagement with self-monitoring in digital weight loss interventions and do not achieve the intended weight loss outcomes, underscoring the need to explore ways to promote sustained engagement in such interventions. Next, it compared the effects of two simplified dietary approaches on engagement with dietary self-monitoring over time and found no between-group differences, suggesting that engagement with dietary self-monitoring may depend upon factors such as the usability and design of the self-monitoring tool rather than the specific dietary approach. Taken together, these findings suggest that efforts to promote engagement in digital weight loss interventions could be targeted to users exhibiting a specific engagement pattern, and that enhancing the user experience of online tools used in digital weight loss interventions may be an important factor for sustained engagement with self-monitoring.

The results of Study One demonstrate a need for consistency in categorizing engagement patterns across digital weight loss interventions. Study One found four unique patterns of engagement with self-monitoring over time, and similar patterns of engagement, as well as similar proportions of participants categorized into these engagement patters, have been identified across several studies (Demment et al., 2014; Goh et al., 2015; Lavikainen et al., 2022). The way these engagement patterns are described can vary widely across studies, and consistency in categorizing these engagement patterns could help researchers identify predictors of these patters. Understanding factors that predict the pattern of low/declining engagement that emerged in Study One (exhibited by 48.5% of the sample) could help researchers target efforts to promote sustained engagement with self-monitoring over time, especially after 6 months, which could improve the overall efficacy of digital weight loss interventions. Study One found that younger participants with a higher BMI may be at greater risk for the low/declining engagement pattern, however, future research should explore a wider range of predictors. Future studies could also test adaptive components to help support low/declining engagers once a lapse in self-monitoring occurs.

Study Two found that specific dietary approach did not influence engagement with dietary self-monitoring or adherence to dietary goals in a 3-month dietary intervention with a focus on weight loss. Engagement with dietary self-monitoring similarly declined over time across groups. One possible explanation is that the cumbersome user experience of the mobile-optimized web-based food log developed for this study attenuated overall levels of engagement with dietary self-monitoring. Optimizing the user experience of online tools developed for digital weight loss interventions may be an important factor in promoting engagement in such programs. User-centered design, an iterative design process in which developers focus on the users and their needs in each phase of the design process, could be a useful approach for such optimization. Additionally, qualitative research may provide critical insights into design elements and features that could increase perceived ease of use and perceived usefulness of digital dietary self-monitoring tools, thereby improving participants' attitudes and intentions for long-term engagement. Future research could explore whether further simplifying the food log (e.g. logging either a "red food" or a "green food" rather than searching for specific food items within each category) could enhance user experience. Finally, future studies could include posttreatment measures of overall user experience, perceived ease of use, and perceived usefulness, and examine associations with engagement in digital weight loss interventions.

The ADOPT study was delivered entirely remotely via mobile methods, which holds promise for dissemination across a wide range of populations. One population that could benefit from simplified dietary self-monitoring is postpartum women. Postpartum women are at increased risk for lifetime obesity (Walker et al., 2007), have poor diet quality (Moran et al., 2013; Wiltheiss et al., 2014), and face unique barriers to participating in traditional weight loss programs (Chang et al., 2008). The transition from pregnancy to postpartum has been associated with changes in food choices that can lead to a less healthful diet (George et al., 2005; Moran et al, 2013; Lebrun et al., 2019; Olson, 2005). Additionally, postpartum women have historically low engagement in traditional weight loss programs (Gilmore et al., 2017; O'Toole et al., 2003; Cavallo et al., 2016), likely due to the stress, exhaustion, and lack of time that accompany new motherhood (Chang et al., 2008). Therefore, a remotely delivered digital weight loss intervention utilizing simplified dietary self-monitoring may provide more flexibility for postpartum women to engage in such programs. Future research could also test whether prescriptive goals for red and/or green food consumption enhance glycemic control in women diagnosed with gestational diabetes during pregnancy, who are at higher risk of developing type 2 diabetes later in life. Finding effective ways to facilitate engagement of pregnant and postpartum women in digital weight loss interventions could help to improve the long-term health status of women of reproductive age.

One weakness of the ADOPT study is the high level of attrition. It is possible that remote delivery and limited person-to-person contact contributed to the lack of follow-up at 3 months. Although the ADOPT study included weekly feedback based on dietary self-monitoring and weight data over the past week, the automated nature of this feedback may not have felt personalized enough for some participants. Additionally, since engagement with dietary self-monitoring was a primary outcome of this study, participants were not prompted to open their food log or reminded to self-monitor their diet after the first two weeks of the program. Future studies could incorporate regular prompts to self-monitor and additional intervention components to enhance personalization, such as didactic videos summarizing lesson content, peer-led videos to model key behavioral skills or problem-solving messages, and interactive elements such as polls or a discussion board (Napolitano et al., 2021).

Conclusions

The innovative studies in this dissertation make an important contribution to the literature on engagement in digital weight loss interventions. Given that engagement with self-monitoring consistently declines over time across digital weight loss interventions, and also that engagement with self-monitoring is critical for weight loss success, Study One characterized individual patterns of engagement with self-monitoring that are associated with clinically significant weight loss and identified a need for consistency in categorizing engagement patterns across studies to better target efforts to promote sustained engagement with self-monitoring. Study Two added to the growing body of evidence that simplified dietary self-monitoring of high-calorie red foods in the TLD is effective for both weight loss and improving diet quality, and demonstrated that specific dietary approach does not appear to influence engagement with dietary self-monitoring in a dietary intervention with a focus on weight loss. To promote long-term engagement with self-monitoring and improve the efficacy of digital weight loss interventions, researchers should focus on refining the user experience of the online tools developed for these studies.

APPENDIX 1: ONLINE SCREENING SURVEY

Welcome to the ADOPT **study** screening questionnaire. These questions will take you approximately 10-15 minutes to complete. Once you complete the screener and submit your responses, you will be contacted by a study staff member by phone or by email. If you continue with the screening questions, your responses to the questions will be kept for descriptive purposes.
Do you give your permission to continue with the online questionnaire and to be contacted by study staff if you are determined to be eligible for this study?

☐ Yes ☐ No

- *If yes, continue screener*
- *If no, have message that says "*Thank you for your interest in our program. If you wish to be informed of future studies, click here." Link to www.uncweightresearch.org/participate_cap.asp

1. Do you read, write and speak English?
☐ Yes ☐ No (INELIGIBLE)

2. How did you hear about this program?
☐ Facebook post
☐ Facebook post by friend, family, co-worker, etc.
☐ Email or word of mouth from friend, family, co-worker, etc.
☐ Website: Name: ____________
☐ Email Listserv: If so, which one: _____________
☐ Another study participant
☐ Other (please specify): ______________

The information gathered on this page is collected for descriptive purposes and does not influence your eligibility to participate.

3. Do you consider yourself to be Hispanic or Latino?
☐ Yes ☐ No

4. Which race to do consider yourself to be? (you may choose more than one category):
☐ American Indian or Alaska Native
☐ Asian
☐ Black or African American
☐ Hispanic, Latino, or Cape Verdean
☐ Native Hawaiian or Other Pacific Islander
☐ White
☐ Other (Specify):__________________

5. What is your gender? ☐ Male ☐ Female
6. What is your date of birth? Enter mm/dd/yyyy
[Age automatically calculated]

7. What is your current weight? _______ lbs.

8. What is your height? ____ ft _____ inches

[BMI automatically calculated]
*The formula to calculate BMI is (weight in pounds * 703)/(height in inches * height in inches)*
What was your weight 6 months ago? ____ lbs.

[Percent weight loss in last 6 months automatically calculated]

9. In a typical week, how many days do you do any physical activity or exercise of at least moderate intensity, such as brisk walking, bicycling at a regular pace, and swimming at a regular pace? (This includes brisk walking done as transportation to or from work or class).

☐ None
☐ 1 day per week
☐ 2 days per week
☐ 3 days per week
☐ 4 days per week
☐ 5 days per week
☐ 6 days per week
☐ 7 days per week

10. On the days that you do any physical activity or exercise of at least moderate intensity, how long (in minutes) do you typically do these activities?

__________Minutes

11. Have you ever had or are you currently receiving treatment for any of the following?

a. Diabetes ☐ Yes (INELIGIBLE) ☐ No
b. Hypertension- high blood pressure ☐ Yes (MD CONSENT) ☐ No
c. Hyperlipidemia – high cholesterol ☐ Yes (MD CONSENT) ☐ No
d. Heart attack or stroke ☐ Yes (INELIGIBLE) ☐ No
e. Cancer
- Are you currently diagnosed with or receiving treatment for cancer? ☐ Yes (INELIGIBLE) ☐ No

f. Hospitalization in the past year for depression or other psychiatric disorder? ☐ Yes (INELIGIBLE) ☐ No
g. Schizophrenia or bipolar disorder? ☐ Yes (INELIGIBLE) ☐ No
h. Alcohol or substance abuse? ☐ Yes (INELIGIBLE) ☐ No
i. Anorexia or bulimia? ☐ Yes (INELIGIBLE) ☐ No
(If yes, "Would you like a referral to the UNC Eating Disorders clinic?" If yes, then refer to UNC ED clinic if ED: 966-5217)

12. Has your doctor ever said you have a heart condition <u>and</u> that you should only do physical activity recommended by a doctor?

☐ Yes (INELIGIBLE) ☐ No

13. Do you feel pain in your chest when you do physical activity?
    ☐ Yes (INELIGIBLE) ☐ No
14. In the past month, have you had chest pain when you were not doing physical activity?
    ☐ Yes (INELIGIBLE) ☐ No
15. Do you lose your balance because of dizziness or do you ever lose consciousness?
    ☐ Yes (INELIGIBLE) ☐ No
16. Do you have a bone or joint problem (for example, back, knee or hip) that could be made worse by a change in your physical activity?
    ☐ Yes (MD CONSENT) ☐ No
17. Is your doctor currently prescribing drugs for your blood pressure or heart condition?
    ☐ Yes (MD CONSENT) ☐ No
18. Do you know of <u>any other reason</u> why you should not do physical activity?
    ☐ Yes (INELIGIBLE) ☐ No *If "yes", specify:*

    ____

19. Do you have any health problems that may influence the ability to walk for physical activity?
    ☐ Yes (INELIGIBLE) ☐ No

WOMEN ONLY COMPLETE THE NEXT 3 QUESTIONS

20. Are you currently pregnant? ☐ Yes (INELIGIBLE) ☐ No
21. Have you been pregnant in the last 6 months? ☐ Yes (INELIGIBLE) ☐ No

22. Do you plan on becoming pregnant in the next 6 months?
    ☐ Yes (INELIGIBLE) ☐ No

    [If yes to #22, in order to put on a waitlist if they will soon be past the 6-month mark]
    How many months ago did you deliver? _______ months ago

23. Are you currently a member of another organized exercise program or are you participating in an organized weight reduction program?
    ☐ Yes ☐ No

    If "yes", specify: ____

    If yes, would you be willing to enroll in this study and stop using the other weight loss program?
    ☐ Yes ☐ No (INELIGIBLE)

24. Are you currently taking weight loss medications?
    ☐ Yes ☐ No

    If "yes", specify: ____

    If yes, would you be willing to discontinue use of these medications?
    ☐ Yes ☐ No (INELIGIBLE)

25. Do you have a smartphone that allows you to access the internet and download and use apps?
- ☐ Yes
- ☐ No (*INELIGIBLE*)

26. Do you have a data plan for your smartphone that allows you to access the Internet when not connected to Wi-Fi?
- ☐ Yes
- ☐ No (*INELIGIBLE)*

27. What kind of text messaging plan do you have for your smartphone?
- ☐ Unlimited
- ☐ Set amount of texts per month
- ☐ Pay per text
- ☐ I don't have a text messaging plan

28. Do you own a bathroom scale?

☐ Yes ☐ No

If no, would you be willing to purchase one to use for this study?

☐ Yes ☐ No (INELIGIBLE)

29. Do you know anyone else who is participating in this study?

☐ Yes ☐ No

Name___________________________ Relationship:_______________________

30. (If "yes" to 38) Do they live with you?

☐ Yes (INELIGIBLE) ☐ No

Thank you for completing these questions. In order to complete your eligibility screening, a study staff member will need to contact you by phone. Please enter your contact information below.

First Name:
Last Name:
Email address:
Cell phone number:
Home phone number:
Work phone number:
Mailing address: (street, city, state, zip)

Which is the best phone number to reach you at during business hours (8:00 AM - 5:00 PM)?
☐ Home phone
☐ Work phone
☐ Cell phone
☐ None of these

Which is the best phone number to reach you at during evening hours (5:00 PM to 8:00 PM)?
☐ Home phone
☐ Work phone
☐ Cell phone
☐ None of these

If we call you to follow up about your eligibility, may we leave a message?
☐ Yes
☐ No

Please click "next" to complete the survey.
After Next, this message will appear: Thank you for completing the ADOPT study screening questions. You will be contacted by a member of the study staff with information about your eligibility. Depending on the number of people interested in participating, it may take a few days for us to contact you. If you do not receive a call within 3-4 business days, please call our research center at 919-966-5852.

APPENDIX 2: LIFESTYLE QUESTIONNAIRE AND PROGRAM EVALUATION

1. First, we'd like to get the names and contact information of two people, preferably one within your household if applicable (e.g. roommate, partner, or parent). These will help us reach you in the event that we are unable to contact you.

Below, please list the contact information for one person within your household (or outside of your household if you live alone).

- Contact #1
    - i. Name: ________
    - ii. Cell phone number: _________
    - iii. Home phone number:_________
    - iv. Address:________________
    - v. Email address: ___________
    - vi. Relationship:_______________

Below, please list the contact information for another person close to you.

- Contact #2
    - i. Name:________
    - ii. Cell phone number:_________
    - iii. Home phone number:_________
    - iv. Address:______________
    - v. Email address:_________
    - vi. Relationship:___________

2. What is the highest grade in school you finished? (Choose one)
    - ☐ Finished elementary school (6th grade)
    - ☐ Finished middle school (8th grade)
    - ☐ Finished some high school
    - ☐ High school graduate or G.E.D.
    - ☐ Vocational or training school after high school
    - ☐ Some college (less than 4 years) or Associate degree
    - ☐ College graduate or Baccalaureate degree
    - ☐ Masters (MS) or Doctoral Degree (PhD, MD, JD, etc.)

3. Are you currently: (Please check all that apply)
    - ☐ Working full-time
    - ☐ Working part-time
    - ☐ A full-time student
    - ☐ A part-time student
    - ☐ None of the above

4. If in school, are you:
   - ☐ Freshman
   - ☐ Sophomore
   - ☐ Junior
   - ☐ Senior
   - ☐ Graduate Student

5. Which of these categories best describe your household income for the past 12 months? This should include income (before taxes) from all sources, wages, veteran's benefits, help from relatives, rent from properties and so on.
   - ☐ Less than $5,000
   - ☐ $5,000 through $11,999
   - ☐ $12,000 through $15,999
   - ☐ $16,000 through $24,999
   - ☐ $25,000 through $34,999
   - ☐ $35,000 through $49,999
   - ☐ $50,000 through $74,999
   - ☐ $75,000 through $99,999
   - ☐ $100,000 and greater
   - ☐ Don't know

Weight History

6. What is your current weight? ___________________________________

7. What was your weight 6 months ago? ___________________________________

8. How much weight would you like to lose? (in lbs.) ___________________________________

9. What do you consider to be your ideal weight? (in lbs.)
   ____

Relationship Status

10. What is your current relationship status? (Choose one)
    - ☐ Single or casually dating
    - ☐ In a committed relationship or engaged
    - ☐ Living in a marriage-like relationship
    - ☐ Presently married
    - ☐ Separated
    - ☐ Divorced

Household Members

11. <u>Who currently lives in your home or apartment with you?</u>
   - ☐ Romantic partner or spouse
   - ☐ Friend or roommates
   - ☐ Children
   - ☐ Parent or sibling(s)
   - ☐ Other
   - ☐ No one, I live by myself

12. Is your romantic partner or spouse:
   - ☐ Underweight
   - ☐ Normal Weight
   - ☐ Overweight
   - ☐ Obese

13. How many friends or roommates live with you?
   - ☐ 1
   - ☐ 2
   - ☐ 3
   - ☐ 4+

14. Please indicate their weight status below.

	Underweight	**Normal Weight**	**Overweight**	**Obese**
Friend/Roommate #1	❍	❍	❍	❍
Friend/Roommate #2	❍	❍	❍	❍
Friend/Roommate #3	❍	❍	❍	❍
Friend/Roommate #4	❍	❍	❍	❍

15. Please indicate which of your parents and/or siblings live with you: (Choose all that apply)
    - ☐ Mother
    - ☐ Father
    - ☐ 1 sibling
    - ☐ 2 siblings
    - ☐ 3 siblings

16. Please indicate the weight status of other family members you live with.

	Underweight	**Normal Weight**	**Overweight**	**Obese**
[relationship]	❍	❍	❍	❍
[relationship]	❍	❍	❍	❍
[relationship]	❍	❍	❍	❍

<u>Health Behavior Questionnaire (Baseline Only)</u>

1. In the past month, how often have you weighed yourself? (Check the answer that best applies).
    - ☐ Several times/day
    - ☐ One time/day
    - ☐ Several times/week
    - ☐ One time per week
    - ☐ Less than one time/week
    - ☐ Less than one time per month
    - ☐ I never weigh myself

2. Do you currently use chewing tobacco, snuff, snus, pipes, cigars, e-cigarettes, or any other tobacco product other than cigarettes?
    - ☐ Yes
    - ☐ No

3. Do you currently smoke cigarettes every day, some days, or not at all?
    - ☐ Every day
    - ☐ Some days
    - ☐ Not at all

4. IF “Yes” to 2, or “Everyday” or “Some days” to 3: How long have you smoked or used tobacco products?
    - ☐ Less than a year
    - ☐ 1 year
    - ☐ 2-3 years
    - ☐ 4-5 years

- ☐ More than 5 years

5. Have you smoked cigarettes in the past, but no longer smoke?
   - ☐ Yes
   - ☐ No

6. During the past 30 days, have you had at least one drink of any alcoholic beverage such as beer, wine, a malt beverage or liquor?
   - ☐ Yes
   - ☐ No
   - ☐ IF NO, skip to end

7. During the past 30 days, how many days did you have at least one drink of any alcoholic beverage? ____

8. One drink is equivalent to a 12-ounce beer, a 5-ounce glass of wine, or a drink with one shot of liquor. During the past 30 days, on the days when you drank, about how many drinks did you drink on average? _____

9. Considering all types of alcoholic beverages, how many times during the past 30 days did you have 4 or more drinks on one occasion? (5 or more for men) _____

10. During the past 30 days, what is the largest number of drinks you had on any occasion? _____

Medication Use

11. Are you <u>currently</u> taking any of the following types of medication (if YES, list the name of the medication you take):

a. Weight Loss Pill Name of Medication:	☐ Yes	☐ No
b. Antidepressant Name of Medication:	☐ Yes	☐ No
c. Diuretics (Water Pill) Name of Medication:	☐ Yes	☐ No
d. Laxative Name of Medication:	☐ Yes	☐ No
e. Steroid (e.g., Prednisone) Name of Medication:	☐ Yes	☐ No

12. Are you taking any medications to control the following conditions? If yes, please indicate type:

a. Diabetes (ex insulin or oral pills): __________________________
b. High blood pressure: __________________________
c. Cholesterol: __________________________
d. Thyroid disorder: __________________________

13. Are you taking any other medications? If yes, please indicate here: _________________

Technology Use

14. What type of Smartphone do you have?
- ☐ Android
- ☐ iPhone
- ☐ Windows
- ☐ Blackberry
- ☐ Other: ___________
- ☐ Don’t Know

15. How often do you use your smartphone to access the internet or check your email?
- ☐ Several times a day
- ☐ About once each day
- ☐ Every few days
- ☐ About once per week
- ☐ Less than once per week
- ☐ Never

16. How many text messages do you send each week?
- ☐ None
- ☐ 1-25
- ☐ 26-50
- ☐ 51-100
- ☐ More than 100

17. Do you currently own a bathroom scale?
- ☐ Yes
- ☐ No

Paffenbarger Physical Activity Questionnaire

1. Was there anything about the past week that made exercising especially difficult for you in terms of extended illness, injury, or vacation?

	YES
	NO

- If "yes", please complete this questionnaire about the previous "typical" week that occurred within the past 30 days.
- If "no", please complete this questionnaire about this past week.

2. We are interested in the number of flights of stairs you climbed on average each day in this week (the week confirmed in question 1). We only want to know the number of flights going <u>UP</u>, not down.

**When answering this question: one flight of stairs = about 10 steps.*

	flights per day

3. We want to know how much time you spent this week (the week confirmed in question 1) brisk walking for exercise or transportation. We are interested in bouts of walking that were at least 10 continuous minutes in duration. *This would include walking outside, at an indoor facility, or on a treadmill.*
   a. How many days this week did you walk briskly for the purpose of exercise or transportation for at least 10 continuous minutes outside, at an indoor facility, or on a treadmill?

	days in the past week

   b. On these days in which you walked briskly at least 10 continuous minutes, on average, how many minutes per day did you walk briskly?

	minutes per day

4. Were there any other sports, fitness or recreation activities in which you participated during this week (the week you confirmed in question 1). We are interested only in time that you were physically active while performing the activity. ALL WALKING SHOULD BE INCLUDED IN ITEM 3.

*NOTE: Do not include "occupational" or "job related" activity as these are not considered to be sport, fitness, or recreational activity.
*NOTE: Household activities such as cleaning, laundry, yard work and gardening are NOT to be included here as they are not considered to be sport, fitness, or recreational activity.

Sport, Fitness, or Recreation	Days per week	Average Time per Day
a.		
b.		
c.		

d.		
e.		
f.		

5. Would you say that during this week you were:

	less active than usual
	more active than usual
	about as active as usual

6. At least once per week, do you engage in regular activity similar to brisk walking, jogging, bicycling, etc. long enough to work up a sweat, get your heart thumping, or get out of breath? :

	YES
	NO

If "yes", please indicate the number of days per week: ☐

<u>Diet Satisfaction Questionnaire (3-months Only)</u>

	Disagree Strongly	Disagree	Neither agree nor disagree	Agree	Agree Strongly
1. I have a lot of energy.	☐1	☐2	☐3	☐4	☐5
2. I feel good about myself.	☐1	☐2	☐3	☐4	☐5
3. I think that I eat a healthy diet.	☐1	☐2	☐3	☐4	☐5
4. I believe that I am reducing my risk for disease by the way that I eat.	☐1	☐2	☐3	☐4	☐5
5. I believe that I am reducing my risk for disease by the way that I exercise.	☐1	☐2	☐3	☐4	☐5
6. I think that I have a healthy lifestyle.	☐1	☐2	☐3	☐4	☐5
7. I am satisfied with my current diet.	☐1	☐2	☐3	☐4	☐5
8. The way that I currently eat makes me feel guilty.*	☐1	☐2	☐3	☐4	☐5
9. The way I currently eat prevents me from eating in restaurants frequently.*	☐1	☐2	☐3	☐4	☐5
10. When dining out, I can easily choose foods from the menu that fit into my current diet.	☐1	☐2	☐3	☐4	☐5
11. Finding appropriate food choices at restaurants is difficult.*	☐1	☐2	☐3	☐4	☐5
12. I have difficulty finding the foods I want when eating out.*	☐1	☐2	☐3	☐4	☐5
13. I feel that I spend a large amount of my budget on the foods that I eat.*	☐1	☐2	☐3	☐4	☐5
14. I think that preparing food and meals for the way I eat now is economical.	☐1	☐2	☐3	☐4	☐5
15. I think that preparing food and meals for the way I eat now costs a lot of money.*	☐1	☐2	☐3	☐4	☐5
16. I spend a lot of money on food.*	☐1	☐2	☐3	☐4	☐5
17. It is hard for me to afford the kind of foods that I eat.*	☐1	☐2	☐3	☐4	☐5
18. Thoughts of food are always on my mind.*	☐1	☐2	☐3	☐4	☐5
19. I think about food between almost every meal.*	☐1	☐2	☐3	☐4	☐5
20. I have cravings for some of my favorite foods.*	☐1	☐2	☐3	☐4	☐5
21. I always feel like I want to snack between meals.*	☐1	☐2	☐3	☐4	☐5

22. I often feel hungry.*	☐1	☐2	☐3	☐4	☐5
23. I feel that my diet controls my life.*	☐1	☐2	☐3	☐4	☐5
24. I spend a lot of time planning my meals.*	☐1	☐2	☐3	☐4	☐5
25. I spend a lot of time shopping for food.*	☐1	☐2	☐3	☐4	☐5
26. I think preparing foods and meals for the way I eat now is time-consuming.*	☐1	☐2	☐3	☐4	☐5
27. I think preparing food and meals for the way I eat now requires a lot of effort.*	☐1	☐2	☐3	☐4	☐5
28. I spend a lot of time looking for new ideas for food and meals that fit into my current diet.*	☐1	☐2	☐3	☐4	☐5

*Indicates reverse scoring

Program Evaluation – Questions 3 Months Only

1. Over the last 3 months, how often did you weigh yourself? (Choose one response)
    - Every day
    - Several times/week
    - One time/week
    - Less than 1 time/week
    - Never weighed myself

2. How difficult was it to make the prescribed changes in your diet over the last 3 months?

1	2	3	4	5	6	7	8
Very easy							*Very difficult*

For those who respond with 5 or above:

It was difficult for me to make changes in my diet because…	Strongly disagree	Somewhat disagree	Neither agree or disagree	Somewhat agree	Strongly agree
a. I/my family did not like the food options available on this plan	1	2	3	4	5
b. I was too hungry	1	2	3	4	5
c. I lacked time due to work, school, or household duties	1	2	3	4	5
d. This plan was too expensive for me	1	2	3	4	5

e. Are there any other reasons that made it difficult to make the prescribed changes in your diet over the last 3 months? If so, please describe:

____

3. How confident are you that if you maintain the changes you've made in your diet, you will be able to maintain your weight or lose more weight?

1	2	3	4	5	6	7	8
Not confident							*Very confident*

4. How satisfied are you with what you've achieved in this program?

1	2	3	4	5	6	7	8
Not satisfied							*Very satisfied*

5. How confident are you that you will continue to follow the approach to eating you were taught during this program?

1	2	3	4	5	6	7	8
Not confident						*Very confident*	

6. Please indicate whether you found the ADOPT program to be:

a. **Flexible**

1	2	3	4	5	6	7	8
Strongly disagree							*Strongly agree*

b. **Structured**

1	2	3	4	5	6	7	8
Strongly disagree							*Strongly agree*

c. **Realistic**

1	2	3	4	5	6	7	8
Strongly disagree							*Strongly agree*

d. **Hard to follow**

1	2	3	4	5	6	7	8
Strongly disagree							*Strongly agree*

e. **Depriving**

1	2	3	4	5	6	7	8
Strongly disagree							*Strongly agree*

f. **Manageable**

1	2	3	4	5	6	7	8
Strongly disagree							*Strongly agree*

g. **Straightforward**

1	2	3	4	5	6	7	8

Strongly disagree *Strongly agree*

h. **Complicated**

1 2 3 4 5 6 7 8
Strongly disagree *Strongly agree*

i. **Too Intensive**

1 2 3 4 5 6 7 8
Strongly disagree *Strongly agree*

7. How difficult was it to track your eating behaviors over the last 3 months?

1 2 3 4 5 6 7 8
Very easy *Very difficult*

System Usability

8. How helpful were the following features of the ADOPT program for pursuing your goal to eat healthier?					
	Not at all helpful	A little helpful	Moderately helpful	Very helpful	I didn't use this feature
a. *Weekly lessons*	1	2	3	4	0
b. *Weekly feedback on your progress*	1	2	3	4	0
c. *Traffic Light Food Log*	1	2	3	4	0
d. *Daily red food limit (RED group) Daily green food goal (GREEN group)*	1	2	3	4	0
e. *Weekly weight check-in*	1	2	3	4	0

The next questions are about the ADOPT **lessons**.

9. How much of the lessons did you usually read?
   - None (1)
   - A little (2)
   - Some (3)
   - All/Most (4)

The next questions are about your ADOPT **feedback**.

10. How much of your feedback did you usually read?

- None (1)
- A little (2)
- Some (3)
- All/Most (4)

11. Below is a list of statements about the feedback on the ADOPT app. Please mark one per line to indicate your response as it applies to the information in the feedback. I found the feedback to be...

	Not at All (1)	A little (2)	Somewhat (3)	Very Much So (4)	Completely (5)	Don't Know (6)
Designed especially for me and my needs (1)						
Important to me personally (2)						
Applies to my life (3)						
Caused me to make positive dietary choices (4)						
Motivating (5)						

The next questions are about your experience with the Traffic Light Food Log.

12. How helpful was the Traffic Light Log for you in helping you pursue your weight loss goal?

	1	2	3	4	5	6	7	8
Very difficult: Very easy	•	•	•	•	•	•	•	•

Please answer the following questions on a scale of 1 to 5 (1 = *strongly disagree*, 5 = *strongly agree*).

13. How easy was it to learn how to use the Traffic Light Log?

	1	2	3	4	5	6	7	8
Very difficult: Very easy	•	•	•	•	•	•	•	•

14. How likely are you to continue to use the food tracking approach to dietary changes after the program?

	1	2	3	4	5	6	7	8
Very unlikely: Very likely	•	•	•	•	•	•	•	•

15. Would you recommend the program you received from ADOPT to others?
    - ○ Definitely not (1)
    - ○ Probably not (2)
    - ○ Probably would (3)
    - ○ Definitely would (4)

For those who respond 1 or 2: Please tell us why you would not recommend the program to others

____

16. Do you have any additional feedback about the ADOPT program?

____

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