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Validation of the strategies for weight management questionnaire for overweight or obese adults /

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Validation of the Strategies for Weight Management Questionnaire for Overweight or Obese Adults

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy

in

Public Health (Health Behavior)

by

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2014

The Dissertation of Julia Karen Kolodziejczyk is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

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LIST OF ABBREVIATIONS

SWM= Strategies for Weight Management Questionnaire

EFA= exploratory factor analysis

CFA= confirmatory factor analysis

PA= physical activity

SCT= social cognitive theory

EBI= Eating Behavior Inventory

SMART= Social and Mobile Approaches to Reduce Weight Study

UCSD= University of California, San Diego

SDSU= San Diego State University

CSUSM= California State University, San Marcos

BMI= Body Mass Index

CFI= comparative fit index

SRMSR= standardized root mean square residual

RMSEA= root mean square error of approximation

GED= General Education Development

ANOVA= analysis of variance

DHQ= Diet History Questionnaire

PPAQ= Paffenbarger Physical Activity Questionnaire

MET= metabolic equivalent

OR= odds ratio

R^2= coefficient of determination

CHAID= chi-square automatic interaction detection

SD= standard deviation

CI= confidence interval

DF= degrees of freedom

LIST OF SYMBOLS

χ^2/df = chi-square/degree of freedom ratio

α= Cronbach's alpha

η^2= eta squared

Φ= phi coefficient

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ABSTRACT OF THE DISSERTATION

Validation of the Strategies for Weight Management Questionnaire for Overweight or Obese Adults

by

Julia Karen Kolodziejczyk

Doctor of Philosophy in Public Health (Health Behavior)

University of California, San Diego, 2014

San Diego State University, 2014

Professor Kevin Patrick, Chair

The aim of this research is to validate the Strategies for Weight Management (SWM) questionnaire. The SWM is a 35-item self-report measure that assesses the use of recommended behavioral strategies for reducing energy intake and increasing energy expenditure to promote weight management in overweight/obese adults. Exploratory (EFA) and confirmatory (CFA) factor analyses were conducted on the SWM. Baseline data were collected from 404 young adults (mean age=22±3.8 years, 70% female, 68% ethnic minority) for the EFA and 236 adults (mean age=42±11.1 years, 75% female, 84% ethnic minority) for the CFA. Both samples were involved in randomized controlled behavioral weight loss interventions aiming to improve diet and physical activity. Correlate models were conducted using linear regressions to assess associations between SWM subscale/total scores and demographics. Reliability (Cronbach's α) and concurrent, predictive, and construct validity were assessed with the young adult sample. Validity tests conducted with linear regressions examined associations between the SWM and weight management outcomes (i.e., weight and self-reported diet and physical activity) using baseline and 6-month data. Signal detection analysis was conducted to identify subgroups of overweight/obese young adults more or less likely to lose ≥5% body weight in 6 months. SWM items and subscale/total scores were predictor variables. Final subgroups were compared by demographics. EFA and CFA suggested a four-factor model: strategies categorized as targeting 1) energy intake, 2) energy expenditure, 3) self-monitoring, and 4) self-regulation. Correlate models revealed weak associations with demographics. Cronbach's α for subscale/total scores ranged from 0.74–0.85. Subscale/total scores predicted select concurrent, predictive, and construct relationships. Signal detection identified three SWM items that best predicted weight loss success, with success ranging from 5.5%–45.8%. Subgroups did not differ by demographics. The SWM showed promising psychometric qualities in two diverse samples of overweight/obese adults. Use of the SWM may promote weight management and ultimately provide a better understanding of the recommended strategies associated with improved weight management.

Chapter 1: Exploratory and Confirmatory Factor Analyses and Demographic Correlate Models

1.1 Introduction

The increasing prevalence of overweight and obesity is a major public health problem[1]. In the United States, 68% of adults are overweight or obese, and by 2030 experts project 50% will be obese[2]. Obesity is a serious concern because it is linked to a number of adverse mental and physical health outcomes, such as cardiovascular disease, certain cancers, type 2 diabetes, depression, and sleep disorders[3]. As obesity negatively affects health[3], healthy weight management is of considerable public health importance.

It is well known that a positive energy balance is a root cause of overweight and obesity[4]. A positive energy balance primarily occurs from the overconsumption of an energy dense diet and inadequate energy expenditure[5,6]. On the other hand, a negative energy balance causes weight loss. Research indicates that weight management behaviors, also known as lifestyle modifications, such as improved diet and increased physical activity (PA)/reduced sedentary behavior, are effective methods to create long-term clinically significant weight loss[7–9]. In fact, some research has shown lifestyle modification to be more effective than pharmacologic methods for weight loss[8,10]. Therefore, to prevent and treat obesity, it is imperative that researchers design effective interventions that help individuals apply strategies that promote healthy weight management.

Self-report weight management questionnaires that assess use of recommended behavioral strategies to reduce energy intake and increase energy expenditure can be used to evaluate the effectiveness of weight management interventions and to tailor intervention content. Tailoring interventions is a commonly used technique to individualize behavior change programs. A tailored approach to weight management behavior change entails designing intervention content for an individual based on his or her specific barriers to weight management[11]. Since the introduction of tailoring in the early 1990s, more than 100 studies of tailoring effects have been published in peer-reviewed scientific journals, and all but a few of these studies showed that tailored interventions are more efficacious than untailored ‘one-size-fits-all’ approaches[12].

The National Heart Lung and Blood Institute Diet Working Group from the Early Trials (i.e., a consortium of weight-loss studies focused on obesity among young adults) created a self-report questionnaire titled thse Strategies for Weight Management (SWM). The SWM has 35 questions that assess use of recommended strategies to promote reduced energy intake and increased energy expenditure related to weight management. It was informed by social cognitive theory (SCT)[13]. SCT is a widely used social and cultural-based theory in health behavior research. A key component of SCT is that human behavior is explained in terms of a reciprocal model in which behavioral capacities (e.g., knowledge, skill), personal factors (e.g., goal-directed behavior, self-efficacy, self-regulation), and environmental influences (e.g., physical, social) interact. Table 1.1 shows how the SWM items reflect SCT's theoretical components. Development of the SWM was inspired by the 26-item Eating Behavior Inventory (EBI), a widely used self-report questionnaire developed in the 1970s that assesses use of recommended behavioral strategies to promote reduced energy intake and weight management in adults[14]. The SWM is different from the EBI because the SWM contains both additional and updated eating behavior and energy expenditure strategies. However, the SWM has not been validated.

One approach to construct validity is to evaluate the internal structure of a questionnaire by using exploratory and confirmatory factor analyses[15]. Exploratory factor analysis (EFA) can help determine latent factors within a scale and can provide empirical evidence to support the inclusion of an item within a factor[16]. EFA also can be used to identify weak items to refine a questionnaire. Confirmatory factor analysis (CFA) assesses if a proposed model fits the sample data[17].

The aim of these analyses was to conduct exploratory (Study I) and confirmatory (Study II) factor analyses on the SWM with an investigation of the relationships between the resulting factors and demographic variables by using correlate models (Study III).

1.2 Study I: Exploratory Factor Analysis

1.2.1 Methods

Sample

Participants were 404 overweight or obese university students enrolled in the Social and Mobile Approach to Reduce Weight (SMART) study (See Table 1.2). SMART is a 2-year randomized controlled trial using Facebook, mobile apps, text-messaging, and the Internet to promote weight loss in young adults[18]. Participants were from three institutions: (1) University of California, San Diego (UCSD); (2) San Diego State University (SDSU); and (3) California State University, San Marcos (CSUSM). Participants were recruited from May 2011 to May 2013 through the following channels: (1) print advertisements in college newspapers, (2) posting of flyers and posters on the campus, (3) advertising on campus electronic bulletins, (4) online advertisements, (5) the SMART study Web site, and (6) e-mails sent via electronic distribution lists.

At baseline, potential participants were screened for inclusion and exclusion criteria and underwent written informed consent. Individuals were eligible for inclusion criteria if they: (1) were age 18 to 35 years; (2) were enrolled full time at one of the designated campuses: UCSD, SDSU, and CSUSM; (3) were willing to attend required research measurement visits in San Diego during the 2-year study; (4) were overweight or moderately obese: 25.0 to 34.9 Body Mass Index (BMI) kg/m^2; (5) were a Facebook user or willing to begin; (6) owned a personal computer; and (7) owned a mobile phone and used text-messaging. Individuals were excluded from participation if they: (1) could not provide informed consent; (2) had comorbidities and required immediate sub-specialist referral; (3) met American Diabetes Association criteria for diabetes; (4) had medical conditions that prohibited compliance with study protocol; (5) were taking weight-altering medications; (6) were pregnant or intending to get pregnant during the next 2 years; (7) were enrolled in or planned to enroll in another weight-loss program; or (8) had a household member on the study staff.

The UCSD, SDSU, and CSUSM Institutional Review Boards approved the study protocols. The baseline measurement visit lasted approximately 2.5 hours, and participants received a $40 incentive.

Measures

Each strategy on the SWM was rated on a five-point Likert scale (i.e., 1 = never or hardly ever, 2 = some of the time, 3 = about half of the time, 4 = much of the time, 5 = always or almost always). Respondents selected a response to each item based on their behavior from the "last 30 days". Responses to each item were summed to obtain a total score. Scores range from 35 to 175.

Statistical Analysis

EFA was conducted with SMART baseline data (N=404) using SPSS Statistics version 20 (SPSS Inc., Chicago, Illinois). Preliminary analyses included inter-item correlations, normality, Barlett's test of sphercicity, and the Kaiser-Meyer-Olkin measure of sampling adequacy.

EFA was conducted by using maximum likelihood analysis. After removing items that did not load in the initial EFA, we proceeded to determine the number of factors to extract by examining the scree plot[19], proportion of the variance in the data set, and interpretability of the factors. Interpretability was determined by the following criteria: (1) the variables that load on a given factor share conceptual meaning, (2) the variables that load on different constructs measure different constructs, (3) the rotated factor pattern demonstrates simple structure, and (4) at least three variables load on a factor[20]. Rotation of factors was conducted with Oblimin rotation with Kaiser normalization. Items should have a minimum factor loading of 0.30[15,21]. Inter-factor correlations were assessed to determine the appropriateness of using oblique rotation. Internal consistency of the SWM scales was assessed by using Cronbach's alpha[22]. Values > 0.7 are considered acceptable, and values 0.8 to 0.9 are preferable[23,24]. We also examined the inter-item correlations within each scale. It is suggested that mean inter-item correlations fall within 0.15 to 0.50 for the scale to be considered unidimensional[25]. It also is necessary to examine the range and distribution of these correlations because most correlations should be moderate in magnitude and should cluster narrowly around the mean to ensure unidimensionality[25].

1.2.2 Results

Preliminary analyses determined the data were suitable for EFA. Our sample size exceeded the 5:1 case to item minimum requirement[26]. The inter-item correlations (most coefficients ≥ 0.3), the Kaiser-Meyer-Olkin value (0.87), and Bartlett's test of sphercicity ($p = 0.00$) supported factorability. Most variables were normally distributed; however, six variables had a skewness and/or kurtosis of $> \pm 2$.

After removing seven items that did not load in the initial EFA (i.e., avoided eating while watching TV, drank less alcohol or changed type of drink to reduce calories, used frozen entrees such as Lean Cuisine or Smart Ones, used the stairs instead of the elevator, wore a pedometer, reduced the amount of time spent watching TV, and worked out with a personal trainer) we proceeded to determine the number of factors to extract. Maximum likelihood analysis revealed the presence of seven factors with eigenvalues exceeding one, explaining 26.6%, 8.4%, 6.8%, 5.4%, 4.7%, 4.2%, and 3.9% of the variance. However, three factors did not have a variance greater than 5%, which suggests a four-factor solution. The scree plot revealed a clear break after factor one and another smaller break after factor three. Therefore, we compared the three through seven-factor models.

The four-factor solution was the most parsimonious model based on factor interpretability (See Table 1.3). After removing six items that failed to load in the four-factor model (i.e., shopped when I was not hungry, stored food in containers where it was not readily visible or in a closet cabinet, only ate when I was hungry, followed a structured meal plan, ate less meat, and used home exercise equipment), this model explained 55.17% of the variance. The final item pool included 22 items and resulted in the following simple factor structures: (1) energy intake (eight items), (2) energy expenditure (three items), (3) self-monitoring (four items), and (4) self-regulation (seven items). The four factors were low to moderately correlated ranging from $r = -0.16$ to 0.47, which supports the use of oblique rotation. Cronbach's alpha coefficient for the four scales ranged from $\alpha = 0.77$ to 0.85, indicating strong internal consistency. Mean inter-item correlations were moderately high ranging from $r = 0.34$ to 0.61 and were centered around the mean, indicating unidimensionality.

1.3 Study II: Confirmatory Factor Analysis

1.3.1 Methods

Sample

Participants were a community sample of overweight or obese adults from San Diego, California (N = 236), enrolled in ConTxt, a 12-month text-message–based randomized controlled weight-loss intervention (See Table 1.2). Participants were recruited from September 2011 to March 2013 through the following channels: (1) flyers hanging in the community and passed out at local community events; (2) free and paid advertisements; and (3) advertisements sent through e-mail list serves.

At baseline, potential participants were screened for inclusion and exclusion criteria and underwent written informed consent. Individuals were eligible for inclusion if they: (1) were overweight or moderately obese: 25.0 to 34.9 BMI kg/m^2; (2) were age 21 to 60; (3) had a mobile phone and were either a current user of text-messages or were willing and able to learn; (4) permanently resided in San Diego; (5) intended to stay in the area during the study period; and (6) were willing to attend measurement visits at the research office. Individuals were excluded from participation if they: (1) were pregnant or intending to become pregnant during the study period; (2) had a history of substance abuse or other psychiatric disorder that would impair compliance with study protocol; (3) were taking weight altering medications; (4) were enrolled or planned to enroll in another weight-loss program; or (5) had medical conditions that would limit ability to comply with moderate-intensity PA recommendations.

The UCSD Institutional Review Board approved the ConTxt study. The baseline measurement visit lasted between 2 to 4 hours. Participants were compensated $50 for their time and $15 for transportation.

Statistical Analysis

To confirm the four-factor model a CFA was conducted using ConTxt baseline data (N = 236). Multivariate normality and multicollinearity were assessed. We planned to conduct CFA on the 22 SWM items using maximum likelihood estimation if data were normally distributed. SAS version 9.3 (SAS Institute Inc., Cary, North Carolina) was used for this analysis.

We assessed model fit with four goodness-of-fit indices: (1) chi-square/degree of freedom ratio (χ^2/df) ($p < 0.05$), with a value of < 2.0 indicating good model fit[27]; (2) comparative fit index (CFI), with a value ≥ 0.90 considered ideal[28]; (3) standardized root mean square residual (SRMSR), with a value < 0.05 considered ideal[28]; (4) root mean square error of approximation (RMSEA), with a value < 0.05 considered ideal[28]. A factor loading of above 0.60 is considered ideal, but factors should be retained in the model if significant ($p < 0.05$)[29]. Item reliability and inter-factor correlations were examined before accepting the final model. Item reliability of each indicator variable was assessed with adjusted R^2 values.

1.3.2 Results

The data met the requirements for conducting a CFA with the exception of multivariate kurtosis (Mardia's coefficient = 72.4). Because the assumption of normality was violated, we checked to see if results varied by using a robust ML estimator for non-normal data in Mplus (Muthen & Muthen, Los Angeles, California). Model fit was identical for most fit indices or lower by only 1/100; and therefore, we continued to use SAS to conduct the CFA. Two items were removed from the model: (1) "I left a few bites on my plate" because it was highly correlated (r=0.66) with "If I was served too much, I left food on my plate" and (2) "Shopped from a list" because it had an exceptionally low loading (0.26). After removing these items, goodness of fit indices showed acceptable fit: $\chi^2/df = 2.0$, CFI = 0.90, SRMSR = 0.06, and RMSEA = 0.07 (CI = 0.06 to 0.08). The final model included four factors and 20 items (See Table 1.4). Standardized loadings ranged from 0.33 to 0.86. Item loadings were statistically significant at $p < 0.05$. Inter-scale correlation coefficients ranged from 0.38 to 0.65, indicating the scales are not orthogonal. R^2 values ranged from 0.11 to 0.74.

1.4 Study III: Correlate Models

1.4.1 Methods

Linear regressions were performed to assess the association between SWM factor and total scores and demographic variables of SMART (N = 404) and ConTxt (N = 236) participants. SAS version 9.0 was used. The following independent variables were used: gender, age, BMI (kg/m^2), education level, relationship status, income level, and race/ethnicity. Education level was an ordinal variable (i.e., ≤ high-school graduate/General Educational Development (G.E.D), education after high school, college graduate/Baccalaureate degree, or Master's/Doctoral degree). Income was a nominal variable (i.e., ≤ $15,999, $16,000–$24,999, $25,000–$34,999, $35,000–$49,999, $50,000–$75,999, ≥ $75,000, and "I don't know/I prefer not to answer"). In the SMART sample the income categories $50,000–$74,999 ($n = 1$) and ≥ $75,000 ($n = 7$) were collapsed for analyses. Gender (i.e., male or female), relationship status (i.e., single or married), and race/ethnicity (i.e., yes/no Hispanic, yes/no White non-Hispanic, yes/no African American, yes/no Asian, and yes/no other) were dichotomous variables. More than one race/ethnicity could apply. Dummy codes were 1 and 0 for each level of the categorical variables. Two-tailed independent sample t-tests and chi-square tests for independence assessed if there were differences between SMART and ConTxt demographic variables.

The dependent variables were SWM scores. Scales were created from the CFA factor solution by summing the un-weighted items representing a factor and dividing by total items answered. Factor scores range from 1 to 5. Factor scores were summed to obtain a total SWM score. Total scores range from 4 to 20.

Bivariate analyses were conducted to determine appropriate variables to include in multivariate models. Spearman correlations were used for continuous (BMI and age were skewed in both datasets), dichotomous, and ordinal variables. One-way analysis of variance (ANOVA) was used for the nominal variable. We used a less conservative p-value of $p < 0.10$ for these bivariate analyses. Co-linearity of the variables was assessed using correlations. Variables correlated > 0.50 were excluded from multivariate models.

Linear regression models examined the association of demographic variables with SWM scores. Non-normally distributed SWM scores were transformed. Variables were entered into the models simultaneously. Variables were significant at $p < 0.05$. Unstandardized parameter estimates and R^2 were reported. Parameter estimates were back log-transformed for interpretation.

1.4.2 Results

Table 1.2 and Table 1.5 display descriptive statistics for demographics and SWM scores, respectively. On average, SMART participants were overweight (BMI < 29.9 kg/m^2). Most SMART participants were female, had some education after high school, and had an income level of ≤ \$15,999. Most SMART participants were white non-Hispanic, followed by equal percentages of Hispanic and Asian race/ethnicities. On average, ConTxt participants were obese (BMI > 30.0 kg/m^2). Most ConTxt participants were female, married, and had an income level of ≥ \$75,000. Most of the ConTxt sample had graduated from high school, with similar percentages of participants who had an education level of some education after high school through Master's/Doctoral degrees. Most ConTxt participants were white non-Hispanic, followed by similar percentages of Hispanic, Asian, and African American race/ethnicities. Demographics of SMART and ConTxt participants were significantly different with the exception of gender and some racial ethnic categories. Average SWM factor scores for SMART and ConTxt participants ranged from 1.7 to 2.7 and the average total score was 9.2. SWM scores from the two samples were not significantly different.

SMART Study

Bivariate analyses revealed that none of the variables were significantly related to factor one (ρ = -0.01 to 0.07). Factor two was significantly related to age (ρ = -0.15, p = 0.00), education (ρ = -0.11, p = 0.02), female gender (ρ = -0.12, p = 0.01), and married relationship status (ρ = -0.11, p = 0.03). Age and education level were significantly correlated > 0.50. Because age was correlated more strongly with factor two than education, education was not included in the regression model. Factor three was significantly related to age (ρ = 0.09, p = 0.09) and Hispanic ethnicity (ρ = -0.14, p = 0.01). Factor four was significantly related to age (ρ = 0.09, p = 0.09), female gender (ρ = 0.16, p = 0.00), and married relationship status (ρ = 0.10, p = 0.04). Total score was significantly related to African American race (ρ = 0.09, p = 0.06). A one-way ANOVA showed income was not significantly related to SWM scores (F = 6, 387, p-values > 0.10).

Final models explained 4%, 2%, 4%, and 1% of the explained variance in the data for factor two, three, four, and total score, respectively (Table 1.6). Results indicated there was a weak negative association between age and factor two. Factor two scores decreased by 0.04 (0.8%) for every year increase in age. There was a weak negative association between gender and factor two. Factor two scores were 0.29 lower (5.8%) for women than men. There was a weak negative association between Hispanic ethnicity and factor three. Factor three scores were 0.06 (5.8%) lower for Hispanics than non-Hispanics. There was a weak positive association between gender and factor four. Factor four scores were 0.06 (6.18%) higher for women than men. The final model for total score was not significant.

<u>ConTxt Study</u>

Bivariate analyses revealed that age was significantly related to factor one ($\rho = 0.18$, $p = 0.01$) and total score ($\rho = 0.12$, $p = 0.08$). Factor two was significantly related to married relationship status ($\rho = -0.13$, $p = 0.04$). Factor three was significantly related to education ($\rho = 0.11$, $p = 0.09$). Factor four was significantly related to age ($\rho = 0.13$, $p = 0.04$), female gender ($\rho = 0.21$, $p = 0.01$), and the "other" race category ($\rho = 0.14$, $p = 0.03$). One-way ANOVAs showed income was not significantly related to SWM scores ($F = 6, 229$, p-values > 0.10).

Final models explained 3%, 2%, and 8% of the explained variance in these data for factor one, two, and four, respectively (Table 1.7). Our results indicated there was a weak positive association between age and factor one. Factor one scores increased by 0.01 (0.2%) for every year increase in age. There was a weak negative association between relationship status and factor two. Factor two scores were lower by 0.06 (5.8%) for married participants than single participants. We found the same weak association between age and factor four that we found for factor one (increase of 0.2%). There was a weak positive association between gender and factor four. Factor four scores were 0.43 higher (8.6%) for women than men. The final models for factor three and total score were not significant.

1.5 Discussion

We found the SWM had four latent factors, categorized as strategies targeting: (1) energy intake, (2) energy expenditure, (3) self-monitoring, and (4) self-regulation. The final questionnaire in this assessment of the internal factor structure included 20 items. CFA identified good fit of this four-factor solution. This is the first study to assess the internal factor structure of the SWM.

We found that strategies characterized as focused on energy intake, energy expenditure, self-monitoring, and self-regulation are latent factors measuring use of weight management behavioral strategies. This is consistent with previous research. Research has shown use of strategies targeting reduced energy intake and increased energy expenditure[8,10,30–32], self-monitoring[33–35], and self-regulation[36–39] is associated with better weight management. These factors are also consistent with the underlying theoretical framework of SCT used to develop the SWM, as self-monitoring and self-regulation are key components of SCT.

Results from the correlate models showed weak associations with certain demographic characteristics and SWM factors. Previous research also has found these associations. In our sample of young adults, use of energy expenditure strategies was negatively associated with age, and energy expenditure scores were lower for females than males. Similar associations with age and gender were observed in two large epidemiological studies involving young adults[40,41]. Our finding that use of self-monitoring strategies were lower for Hispanics than white non-Hispanics also is consistent with some previous research[42]. In our sample of adults, age was positively associated with use of energy intake strategies and self-regulation strategies for weight management, which is congruent with most previous research[38,43–45]. The association that use of energy expenditure strategies was lower for married participants than single participants has been observed in other samples of adults as well[46,47]. In both our samples, men had lower levels of use of self-regulation strategies for weight management than women. Previous research has also reported this association in both young adults and adults[38,48]. The weak associations found from the correlate models suggest that demographics should have little influence on SWM scores. However, these associations were significant, indicating that researchers should control for age, gender, Hispanic ethnicity, and relationship status when using the SWM to assess use of recommended behavioral strategies that promote weight management, especially if using factor level scores.

We expected a negative association between BMI and SWM scores as cross-sectional and longitudinal studies have demonstrated that persons with lower BMI are more likely to use weight management strategies[31,32,34,39]. We may not have found a significant association with BMI and SWM scores because our baseline samples were too homogenous to detect differences. Our samples included only overweight and obese participants. In addition, participants are more likely to report weight management strategies if they complete an intervention encouraging recommended behavioral strategies for weight management. A more heterogeneous sample in regard to BMI and use of weight management strategies probably would result in more variation in item responses, which should show an association between BMI and SWM scores if this relationship exists.

Study limitations and strengths should be noted. First, the fourth factor has the lowest loadings, possibly because the items cover a wide domain. However, as all items were significant, they were retained in the model. Second, there are some low R^2 values, but this is to be expected for loadings < 0.60. Third, items that did not load may suggest there are additional factors that need more items to 'flesh out' the content domain. Fourth, the 35-item SWM measure is not an exhaustive list of weight management strategies; however, it is a comprehensive list of strategies generally recommended in weight-loss interventions. As this measurement tool is intended for use in research, a shorter tool focusing on only the most important strategies may be preferable, as this will reduce unnecessary participant burden. Fifth, the results from the EFA are most applicable to young adults and may not be generalizable to older adult populations. It would have been ideal to use a community-based adult samples for both the EFA and CFA. However, the CFA confirmed the results of the EFA, indicating the factor structure found in the EFA is robust, as it is generalizable to a different type of sample. A strength of these studies is that both samples were ethnically diverse. In addition, use of a young adult sample is an important contribution to weight-loss research because this age group is an especially high-risk population for overweight and obesity[49–52].

It is important to note that in these analyses a summative scoring procedure was used (total score was calculated by adding the factor averages). We do not recommend calculating a total score unless data (a score for at least one item) are available for each factor. Alternatively, if there is a significant amount of missing data all items can be averaged to obtain a total score; however, this scoring approach should be used with caution because we believe each factor is an important dimension of the weight management construct measured in these factor analyses.

The SWM shows promising psychometric qualities, but further validation research should to be completed. The next steps to validate the SWM include validity testing (e.g., concurrent, predictive, construct) using longitudinal data and a variety of outcome measures (e.g., weight, diet, PA) and reliability testing (e.g., internal consistency, test-retest). It would also be useful to conduct factor invariance testing among demographic characteristics. Tests of measurement invariance are an important issue so group comparisons can be made[53]. Meaningful comparisons can only be made if the measure is comparable across different groups. Measurement invariance involves testing the equivalence of measured constructs in two or more independent groups to ensure the same constructs are assessed in each group. Future research should further investigate the factor structure among demographics such as racial and ethnic groups. In addition, a classification tree analysis, a segmentation technique designed to split a sample into two or more categories based on available attributes, could also be conducted to determine how the SWM could be used to tailor intervention content[54]. A tree analysis could identify the SWM items more or less likely to predict weight loss.

Use of the SWM may advance behavioral science because this tool could help researchers create effective approaches to weight management for weight loss among overweight and obese adults. With further validation research, researchers can use the SWM to tailor intervention content and assess the impact of interventions on behavior change. These contributions would be significant because they ultimately could provide improved knowledge about whether use of the recommended strategies promotes healthy weight management.

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Chapter 2: Reliability and Concurrent, Predictive, and Construct Validity

2.1 Introduction

Overweight and obesity is an epidemic affecting two-thirds of the population in the United States[2]. It is associated with an increased risk for many diseases and conditions, including heart disease, high blood pressure, diabetes, and certain cancers[3]. It is recommended that individuals with a Body Mass Index (BMI) greater than 25 kg/m^2 who have weight-related comorbidities lose at least 5% to 10% of their body weight[55–57]. Losing this modest amount of weight can improve cardiometabolic risk factors and may attenuate many negative consequences of obesity and improve health.

It is well known that lifestyle behavior modification that includes reducing energy intake and increasing energy expenditure produces weight loss and should be considered the first line of intervention[10,55,58–60]. To reduce energy intake, obese individual should increase intake of low energy dense foods such as fruit, vegetables, and whole grains and decrease intake of fat and added sugar[61] and increase their awareness of energy content of foods and portion size[62,63]. To increase energy expenditure, individuals are advised to engage in 30 minutes or more of moderate-intensity physical activity (PA) on most days of the week[64,65] and to increase 'lifestyle activities', the PA that can be part of everyday life such as taking the stairs rather than using an elevator[66,67].

Two behavioral strategies in lifestyle modification programs for weight loss are self-monitoring[33–35] and self-regulation[36–39]. Self-monitoring is defined as the systematic recording of weight and target behaviors and is considered an effective component of behavioral treatment[68]. Self-monitoring provides feedback to an individual to improve or maintain target behaviors[68]. For weight control, self-monitoring energy intake, PA, and weight are recommended[33–35]. Self-regulation is another key component to successful weight loss and is defined as self-corrective adjustments taken to stay on track to attain a goal[69,70]. Examples relevant to weight control include reducing portion sizes or changing food preparation techniques.

The Strategies for Weight Management (SWM) measure is a self-report questionnaire assessing use of these types of lifestyle modification strategies. It includes 20 strategies usually recommend interventions to promote weight management. Items are categorized within the following four domains: 1) energy intake, 2) energy expenditure, 3) self-monitoring, and 4) self-regulation. The development of the SWM, including an assessment of its factor structure, has been described previously (author name removed, under review, 2013). To date there is no validated questionnaire similar to the SWM. Other questionnaires that assess diet and energy expenditure behaviors measure food intake patterns or time spent in PA as opposed to behavioral strategies to improve weight management [71,72].

The aim of the current study is to assess reliability and concurrent, predictive, and construct associations of this measure with weight, diet, and PA variables involving a diverse sample of adults.

2.2 Methods

2.2.1 Design

The Social and Mobile Approach to Reduce Weight (SMART) study is a randomized controlled trial testing the efficacy of an intervention that aims to promote weight loss in overweight or obese young adults. The primary goal of the intervention is 5% to 10% weight loss at 24 months. Participants were randomized to either the treatment (n = 202) or comparison group (n= 202). The proposed analyses will use data from the baseline and six-month assessments. The measurements used in these analyses represent serial and intermediate measurements from the 24-month trial. SMART has been described in detail previously[18].

2.2.2 Sample

A total of 404 overweight or obese university students were enrolled (See Table 1). Participants were recruited from: (1) University of California, San Diego (UCSD); (2) San Diego State University (SDSU); and (3) California State University, San Marcos (CSUSM). They were recruited from May 2011 to May 2012 through campus advertising, such as advertisements in college newspapers and list-serve e-mails (i.e., 1,941 individuals were interested in the study).

Individuals were screened for inclusion and exclusion over the phone. Individuals eligible for inclusion were: (1) age 18 to 35 years; (2) enrolled full-time at one of the designated campuses; (3) willing to attend required research measurement visits in San Diego over the two-year study; and (4) overweight or moderately obese (25.0 to 34.9 BMI kg/m^2)[73]. Individuals were excluded from participation if they: (1) could not provide informed consent; (2) had comorbidities and required immediate sub-specialist referral; (3) met the American Diabetes Association criteria for diabetes; (4) had psychiatric or medical conditions that prohibited compliance with study protocol, prescribed dietary changes, or moderate PA; (5) were using weight-altering medications; (6) were pregnant or intending to get pregnant over the two-year period; or (7) were enrolled in/planned to enroll in another weight loss program. At baseline, individuals were re-screened for inclusion and exclusion criteria by measurement staff and underwent written informed consent.

Data collection occurred at Moore's Cancer Center at UCSD and Student Health Services at SDSU and CSUSM. The UCSD, SDSU, and CSUSM Institutional Review Boards approved study protocols, which are in compliance with the Health Insurance Portability and Accountability Act. Participants received a $40 incentive at baseline and $50 at six months. Twenty-three participants were lost to follow up at six-months.

2.2.3 Intervention

The SMART intervention was informed by social cognitive theory[74], control theory[75], and ecological theory[76]. Five core strategies from these theories (i.e., self-monitoring, intention formation, goal setting, goal review, and feedback) were embedded in intervention activities to maximize the effect of the intervention. Participants in the intervention group received a tailored behavioral weight loss curriculum via Facebook, smartphone applications, text-messages, blogs, e-mail, and health coach 'lifelines'. Participants were asked to interact with at least one intervention modality a minimum of five times per week.

2.2.4 Comparison Group

Participants assigned to the comparison group had access to a website without social networking components that contained general health information relevant to young adults (e.g., stress management, sexual health, alcohol). This website included some diet, PA, and sedentary behavior weight loss recommendations comparable to what individuals would receive from their primary care providers, but it did not include health behavior recommendations. Participants assigned to the comparison group were instructed to interact with at least one intervention modality weekly.

2.2.5 Measures

Measurements were conducted by trained measurement staff blind to intervention randomization. These staff administered questionnaires. Incoming data were checked first by measurement staff, and they were instructed to contact participants immediately to recover missing data.

Weight (kg) was measured to the nearest 0.01-pound using a calibrated digital scale. Measurement staff weighed the participant twice and took the average of the two readings. Percent weight change from baseline to six months was calculated as (negative percentages indicate weight loss).

The SWM questionnaire (see Appendix I) is composed of four subscales: (1) energy intake, (2) energy expenditure, (3) self-monitoring, and (4) and self-regulation. These subscales were determined from factor analyses described in previous research (author name removed, under review, 2013). Respondents were asked to select a response to each item based on their behavior from the "last 30 days". Each item on the SWM was rated on a five-point Likert scale (i.e., one = "hardly or never" and five = "always or almost always"). Items within each subscale are summed and divided by total items answered. Subscale scores range from 1 to 5. Subscale scores are summed to obtain a total score, and all subscale scores must be available to obtain a total score. Total scores range from 4 to 20.

The Diet History Questionnaire II (DHQ II) was used to obtain dietary data. The DHQ is a widely used food frequency questionnaire (FFQ) that was developed by staff at the Risk Factor Monitoring and Methods Branch at the National Cancer Institute. The DHQ I was updated to the DHQ II with minimal modifications to the food list and the nutrient database. The DHQ II consists of 124 food items and includes portion size. Correlations for energy intake between truth (estimated by using a measurement error model based on repeat 24-hour recalls collected over the course of one year) and the DHQ I were $r = 0.49$ in men and $r = 0.48$ in women[77]. There have not been validation studies with the DHQ II because validation findings are unlikely to be greatly modified by the minimal modifications made. The nutrient and food group database, created for analyzing the DHQ II, is based on that used for national 24-hour dietary recall data from the National Health and Nutrition Examination Surveys[78]. The time reference for the DHQ II is “in the last month”. The DHQ II was used to estimate the following diet variables: (1) percent of energy from dietary fat; (2) percent of whole grains of total grains; vegetables, excluding legumes (c); (3) fruit (c); (4) discretionary oil and solid fat (g) (i.e., fat that is added to food, such as butter); and (5) added sugar (t). Participants with unreliable total energy intake were removed from the analyses (i.e., < 800 kcal/d or > 5000 kcal/d for men and < 600 kcal/d or > 4000 kcal/d for women).

Paffenbarger Physical Activity Questionnaire (PPAQ) is a self-report measure that assesses weekly leisure time energy expenditure in adults[79,80]. Two items on this questionnaire were used that asked respondents to estimate the number of blocks walked and to list sports or exercise in which they had participated during the past week as well as the frequency and duration. For each sport or exercise listed, energy expenditure (kcal) was calculated from the respective metabolic equivalent (MET) intensity level[81]. Total leisure time energy expenditure per week in kcals and minutes per week were calculated. The PPAQ has been validated with cardiorespiratory fitness measures, accelerometers, daily PA logs, and various health outcomes and is believed to be a good measure of moderate and vigorous intensity PA[82–84]. One-month test-retest reliability was acceptable ($r = 0.72$)[82].

2.2.6 Statistical Analysis

Reliability of SWM subscales and total score was examined in terms of internal consistency using Cronbach’s alpha values[22]. The corrected item-total correlation, which indicates the degree to which each item correlates with the total score, was used to assess whether items should be removed.

Linear regression models were used to examine concurrent, predictive, and construct validity ($p < 0.05$). Dependent variables were transformed to improve their fit to Gaussian distributions. If variables were non-normal (skewness or kurtosis > ±3.0) after transformation, they were made into dichotomous variables (i.e., split between negative/zero and positive values) and logistic regressions were conducted. Variables were entered into the models simultaneously. SPSS Statistics version 22 (SPSS Inc., Chicago, Illinois) was used.

To provide an unbiased summary of validity evidence, percentages were reported for each type of validity and scores (i.e., each subscale and total score). Percentages were calculated by counting the number of outcomes that support validity (i.e., tests that were significant and in the expected direction) versus the total number of tests. For divergent validity, percentage of outcomes that were non-significant were calculated. To assess the strength of validity results, the following percentage ratings were used: < 40% poor, 40% to 70% good, and ≥ 70% excellent.

Concurrent, predictive, and construct validity was assessed between SWM scores and the following outcome variables: (1) weight, (2) diet variables, and (3) energy expenditure variables. To assess concurrent validity, the associations between baseline SWM scores (i.e., total and subscales) and baseline scores for each outcome variable were examined. To assess predictive validity, the associations between baseline SWM scores and change scores for each outcome variable were examined. Change scores were calculated as the six-month score minus the baseline score. To assess construct validity I (i.e., sensitivity to the study treatment condition), the associations between SWM change scores on group (treatment vs. control) were examined. To assess the construct validity II (i.e., relationship to the outcomes), the associations between change scores for each outcome variable on change in SWM scores were examined. It is important to note that the construct associations tested the hypothesized 'casual chain' (i.e., it is hypothesized that intervention condition will affect weight behaviors and weight behaviors will affect outcomes). Divergent validity was assessed by testing the relationship between: (1) PA variables and the energy intake and self-regulation subscales, and (2) diet variables and the energy expenditure subscale.

Descriptive statistics were reported for SWM scores and outcome variables. Means and standard deviations were reported for continuous variables, and N and percent were reported for other variables. Paired-sample t-tests were used to assess mean differences between baseline and six-months for normally distributed data, and Wilcoxon signed rank test was used for non-normal data.

Covariates included self-reported gender, age, education level, relationship status, income level, and race/ethnicity (See 2.1). Age was a continuous variable, education level was an ordinal variable, income was a nominal variable. Gender, relationship status (i.e., single, in a committed relationship), and race/ethnicity were dichotomous variables. Bivariate analyses between SWM factors and total score and possible covariates were conducted to determine appropriate variables to include in multivariate models. Spearman correlations were used for continuous (age was non-normally distributed), dichotomous, and ordinal variables. One-way analysis of variance (ANOVA) was used to determine the relationship between the SWM factors and total score and the nominal variable. Variables significantly related to SWM scores at $p < 0.10$ were included in multivariate models using the corresponding SWM factor or total score as either the independent or dependent variable. Co-linearity of the variables was assessed using correlations (variables correlated > 0.50 were excluded).

2.3 Results

SMART participants were overweight, female, had some education after high school, and had an income level of ≤ $15,999 (Table 2.1). Twenty-four participants (5.9%) were removed from the diet-related analyses for unreliable energy intake values at baseline and forty-one at six months (12.9%). Table 2.2 displays the baseline and six-month descriptive statistics for the SWM scores and diet and PA variables.

2.3.1 Reliability

Cronbach's alpha coefficient was $\alpha = 0.85$ for the energy intake subscale (corrected item-total correlations 0.48 to 0.72), $\alpha = 0.83$ for the energy expenditure subscale (corrected item-total correlations 0.60 to 0.77), $\alpha = 0.76$ for the self-monitoring subscale (corrected item-total correlations 0.45 to 0.72), $\alpha = 0.74$ for the self-regulation subscale (corrected item-total correlations 0.40 to 0.66), and $\alpha = 0.89$ for the total scale (corrected item-total correlations 0.31 to 0.69).

2.3.2 Validity

Bivariate Analyses

Bivariate analyses indicated covariates to include in multivariate models. There were no significant associations between the energy intake subscale and covariates ($\rho = -0.01$ to 0.07). Significant associations were found between the energy expenditure subscale and age ($\rho = -0.15$, $p < 0.01$), education ($\rho = -0.11$, $p = 0.02$), female gender ($\rho = -0.12$, $p = 0.01$), and married relationship status ($\rho = -0.11$, $p = 0.03$). However, there also was a significant association between age and education level ($\rho = 0.53$, $p < 0.001$). Because age had a stronger correlation with the energy expenditure subscale than education, age was used instead of education in these multivariate models. Significant associations were found between the self-monitoring subscale and age ($\rho = 0.09$, $p = 0.09$) and Hispanic ethnicity ($\rho = -0.14$, $p = 0.01$). There were significant associations between the self-regulation subscale and age ($\rho = 0.09$, $p = 0.09$), female gender ($\rho = 0.16$, $p = 0.00$), and married relationship status ($\rho = 0.10$, $p = 0.04$). Total score was related significantly to African American race ($\rho = 0.09$, $p = 0.06$). One-way ANOVAs showed non-significant associations between income and SWM scores ($p > 0.10$).

Concurrent Validity

Table 2.3 displays the linear regression results for concurrent validity. Associations between baseline SWM scores and weight were non-significant. The energy intake subscale was related significantly to most of the diet variables in the expected directions. There were significant relationships between the energy expenditure subscale and some of the diet variables. The self-monitoring subscale was not related significantly to the diet variables. The self-regulation subscale was associated significantly with fat intake variables and whole grain intake in the expected directions, but it was not associated significantly with fruit, vegetable, and added sugar intake. There were significant positive associations between SWM scores and both PA variables. Total SWM score had significant associations in the expected directions with most of the diet and PA variables.

Predictive Validity

There were significant negative associations between the energy expenditure subscale and total score and percent weight change from baseline; however, the associations between the energy intake subscale, self-monitoring subscale, and self-regulation subscale and weight loss were non-significant (Table 2.4). Associations between most of the SWM scores and diet variables were non-significant. Associations between SWM scores and both PA variables were non-significant.

Construct I Validity

There were significant positive associations between treatment group and change in the energy intake and self-monitoring subscales and total score but not the energy expenditure and self-regulation subscales (Table 2.5).

Construct II Validity

Table 2.6 displays the linear regression results for construct II validity. There were significant negative associations between most SWM change scores and percent weight change. There were significant associations between change in the energy intake subscale and change in whole grain, vegetable, and added sugar intake, but there were no significant associations with the other diet variables. There were no significant associations between change in the self-monitoring and energy expenditure subscales and change in the diet variables. Change in the self-regulation subscale was not related significantly to change in the diet variables except for negative associations with discretionary fat and added sugar. Change in total score had a significant positive association with change in added sugar, but no other significant associations were found with the other diet variables. SWM scores had significant positive associations with PA variables.

Summary of Validity Evidence

Table 2.7 lists summary percentages by SWM and validity type. All SWM scores showed some evidence of concurrent validity (percentages ranged from 22% to 78%), but only the energy expenditure subscale showed evidence of divergent validity. All scores had <40% evidence of validity for predictive validity, and the energy intake, energy expenditure, and self-regulation subscales had 100% divergent validity evidence. All SWM scores showed some evidence of construct II validity (percentages ranged from 33% to 67%), but only the energy expenditure subscale showed evidence of divergent validity.

2.4 Discussion

This study indicates the SWM is a reliable and valid measure to assess weight management behaviors in adults. Reliability results showed the SWM has good internal consistency. In addition, corrected item-total correlations were > 0.30, indicating none of the items should be removed from the scale(s). Concurrent, predictive, construct I, and construct II validity results showed significant associations between subscales and total score and certain weight-management related outcomes. To our knowledge, this is the first study to assess reliability and validity of the SWM.

2.4.1 Concurrent Validity

There was evidence of concurrent validity between the SWM scores and most of the diet and PA outcomes, with a few exceptions. There was no evidence of concurrent validity between the energy intake subscale and vegetable intake. In addition, the self-regulation subscale showed concurrent validity in the expected direction with fat intake variables and whole grain intake but not with fruit, vegetable, and added sugar intake. These results may be because there is random and systematic errors associated with self-reported dietary intake measuring instruments[85]. This may be especially true when measuring vegetable intake with the DHQ as vegetable intake correlations between the DHQ and four 24-hour dietary recalls were among the lowest versus other food groups[86]. Results indicated that the self-monitoring subscale showed concurrent validity with PA but not dietary intake. These results may have been because participants engaged in more PA monitoring rather than diet monitoring because the latter typically includes recording in more detail, which is a time-consuming, tedious process that is difficult to maintain[35]. Results also showed weak discriminative validity evidence for the subscales. This may be because it is difficult to demonstrate discriminative relationships between diet and PA behaviors as these behaviors often occur simultaneously[87], and there may be additive or synergistic effects[88].

Moreover, there was no evidence of concurrent validity with SWM scores and weight. While cross-sectional and longitudinal studies have demonstrated that individuals with lower weight are more likely to use weight management strategies[31,32,34,39], individuals are more likely to report weight management strategies if they complete an intervention that encouraged recommended behavioral strategies for weight management. Another explanation is that this association may not have been found because both samples included only overweight or obese participants and did not include normal-weight individuals. A more heterogeneous sample in regard to weight probably would result in more variation in item responses, which should show an association between weight and SWM scores.

2.4.2 Predictive Validity

Predictive validity was found between the energy expenditure subscale and total score and percent weight change from baseline, but change in the SWM scores were not predictive of change in dietary intake and PA outcomes. The result that total score predicted weight loss is consistent with previous research as those who improve diet and PA behavior generally have been found to lose more weight compared with those who improve diet alone[89,90].

2.4.3 Construct I Validity

Results showed strong evidence of construct I validity with the energy intake and self-monitoring subscales and total score. These associations were expected because the intervention encouraged participants to engage in weight management strategies, and there was significant weight loss in the treatment group from baseline to six-months. It was expected that all SWM subscales would be associated significantly with treatment group, but there was no evidence of sensitivity to the treatment condition from the energy expenditure or self-regulation subscales. Non-significant results could be the result of less than optimal implementation of the intervention related to energy expenditure and self-regulation strategies.

2.4.4 Construct II Validity

There was strong evidence of construct II validity with change in SWM subscales and total score and change in weight loss and PA outcomes but not diet outcomes. All scores showed evidence of construct II validity with percent weight change, with the exception of the energy expenditure subscale. This non-significant association with the energy expenditure subscale may have been because PA alone, without dietary restriction, usually results in little weight loss[90]. Unexpected results with most of the diet variables were found. Most of the associations between change in the energy intake subscale, self-regulation subscale, self-monitoring subscale, and total score and diet outcomes were non-significant. In addition, participants with higher SWM scores were less likely to have a positive increase in whole grain intake; these results are in the opposite expected direction. As expected, there were significant positive associations between change in the energy expenditure subscale, self-monitoring subscale, and total score and change in both PA variables. Overall, there was weak evidence of discriminative construct II relationships.

2.4.5 Validity Summary Percentages

Concurrent and construct II validity had the strongest validity evidence as most scores had good to excellent percentage ratings. Predictive validity showed the weakest validity evidence as all scores had poor summary ratings. Energy intake, energy expenditure, and self-regulation subscales had good to excellent percentages ratings for at least two types of validity, which suggests these subscales alone can provide a valid assessment of weight management strategies. The energy expenditure subscale is the only subscale that demonstrated good percentage ratings for both validity and divergent validity. Total score showed the strongest validity evidence as this score consistently showed good to excellent validity percentage ratings for most validity types.

2.4.6 Strengths and Limitations

Study limitations and strengths should be noted. These analyses tested the SWM in a diverse sample of adults comprised of 68% ethnic minorities. However, as the sample was mainly young adults, future research should investigate validity and reliability of the SWM in other populations. Various forms of validity were assessed but only one type of reliability as tested. Test-retest is another commonly used analysis to assess reliability that should be explored in future research. Last, future research should replicate this analysis with objective measures of diet and PA, such as blood-based biomarkers and accelerometers.

2.5 Conclusion

The current study indicates the SWM is a reliable and valid measure to assess weight management behaviors in adults. While there was some evidence of concurrent, predictive, construct I, and construct II validity with SWM subscales and diet and PA outcomes, the SWM total score at baseline and six-months consistently predicted weight change. These results indicate that total score follows the intervention causal chain; that is, intervention group was associated with a positive change in total score, and change in total score was associated with weight loss.

Researchers can use the SWM to assess use of behavioral strategies to evaluate effectiveness of weight management interventions and to better understand the mechanisms of weight loss. It also can be used to tailor intervention content. Further research should investigate whether this measure can be used to tailor intervention content as well as to evaluate the effectiveness of weight management interventions.

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Chapter 3: Weight Management Strategies that Predict the Likelihood of Weight Loss among Overweight/Obese Young Adults Using Signal Detection Analysis

3.1 Introduction

Young adults are a high-risk population for overweight and obesity[49–52], as surveys suggest that rates of weight gain are highest among this age group[50,51]. National estimates published in 2009 indicate over 40% of young adults in the United States are overweight/obese[49]. This age group is at high risk for unhealthy weight-related behaviors, such as physical inactivity and unhealthy diet, because of many personal, interpersonal, and environmental factors that typically occur during the transition from adolescence into early adulthood[91,92]. Research has found these behaviors often persist into adulthood[93], and being mildly or moderately overweight at age 20 is linked with substantial incidence of obesity by age 35[52]. Therefore, effective weight loss programs focusing on obesity treatment among young adults are imperative.

Current behavioral weight management programs are not meeting the needs of many young adults. A 2010 review of 14 weight loss interventions enrolling young adults reported a non-significant mean weight loss of only 3.0 kg (95% CI 8.5 to 2.5)[94]. Another review reported that out of six randomized controlled trials published between 1985–2011, most showed significant weight gain prevention compared to comparison groups, but all had low effect sizes[95]. In 2013, another review of randomized controlled trials reported average weight change for young women enrolled in weight loss programs ranged from a low 1.9 kg to +0.1 kg, and more than half of the eight studies had <80% retention[96]. Moreover, data from a pooled analysis of three studies from different regions of the United States found young adults had lower attendance, retention, and weight loss in behavioral weight loss programs compared to older adults[97]. These poor intervention outcomes indicate current weight loss programs are not effective for many young adults who try to lose weight. Understanding the characteristics of individuals who have difficulty losing weight and potentially helpful behavioral strategies may help develop more effective weight loss programs for this target population

Signal detection analysis can be used to identify characteristics of individuals more or less likely to lose weight. This method classifies participants into mutually exclusive and maximally differentiated subgroups based on a dichotomous outcome[54,98]. Information from signal detection can be used to develop an algorithm (in the form of a tree diagram) for assigning individuals to the most appropriate treatment, which can be used in research or clinical settings easily. Signal detection analysis is not affected significantly by co-linearity of variables in the model; therefore, it can handle a large number of variables[99]. This is one reason it is preferred for exploratory data analysis. This method also can identify individuals who are homogenous in both outcome and risk predictors[100], which is preferable for designing tailored interventions. Other benefits of using signal detection include that it is a more powerful method to detect interactions, and it automatically examines all interactions without explicitly including them in a model.

Few researchers have applied signal detection methods to weight loss. One study found predominantly white overweight adults initially satisfied with their body and with no history of repeated weight loss were more likely to lose at least 2 units of body mass index in 1 year[101]. Other research found that among obese adults, Axis I psychiatric disorder diagnoses (e.g., anxiety, mood) enhanced the likelihood of good compliance to treatment but lowered the probability of ≥ 10% weight loss over 8 months[102]. In addition, researchers found predominantly white overweight/obese adult women were more likely to achieve ≥ 5% weight loss in 6 months if they received support from friends for healthy eating and family for PA[103].

To date, no research has applied signal detection methods to explore characteristics associated with the likelihood of weight loss among young adults. The current study aims to overcome this by using signal detection to identify weight management strategies associated with 6-month weight loss in a diverse sample of overweight/obese young adults. This information may help to inform more effective weight loss interventions for this target population.

3.2 Methods

3.2.1 Design

The Social Mobile Approaches to Reduce weighT (SMART) study is a randomized controlled trial testing the efficacy of an intervention aiming to promote weight loss by improving diet and increasing physical activity (PA) in overweight/obese young adults. The primary goal of the intervention is 5% to 10% weight loss at 24 months. Participants were randomized to either the treatment (n = 202) or comparison group (n = 202). The current study used data from baseline and 6-month assessments. Measurements used in these analyses represent

serial and intermediate measurements from the 24-month trial. SMART has been described in detail previously[18].

3.2.2 Sample

A total of 404 overweight/obese university students were enrolled. Participants were recruited from: (1) University of California, San Diego (UCSD); (2) San Diego State University (SDSU); and (3) California State University, San Marcos (CSUSM). They were recruited from May 2011 to May 2012 through various campus advertising including posting of flyers and posters around the campus and advertising on campus electronic bulletins.

Individuals were screened for inclusion and exclusion over the phone. Individuals eligible for inclusion were: (1) age 18 to 35 years; (2) enrolled full time at one of the designated campuses; (3) willing to attend required research measurement visits in San Diego over the 2-year study period; and (4) overweight or moderately obese (25.0 to 34.9 BMI kg/m^2). Individuals were excluded from participation if they: (1) could not provide informed consent; (2) had comorbidities and required immediate sub-specialist referral; (3) met the American Diabetes Association criteria for diabetes; (4) had self-reported psychiatric or medical conditions that prohibited compliance with study protocol, prescribed dietary changes, or moderate PA; (5) were using weight-altering medications; (6) were pregnant or intending to get pregnant over the 2-year study period; or (7) were enrolled in or planned to enroll in another weight loss program. At baseline, individuals were re-screened for inclusion and exclusion criteria by measurement staff and underwent written informed consent.

Data collection occurred at the Moores Cancer Center at UCSD and Student Health Services at SDSU and CSUSM. UCSD, SDSU, and CSUSM Institutional Review Boards approved study protocols. Participants received a $40 incentive at baseline and $50 at 6 months. Twenty-three participants (5.7%) were lost to follow-up at 6-months.

3.2.3 Intervention

The SMART intervention was informed by social cognitive theory[74], control theory[75], and ecological theory[76]. Five core strategies from these theories (i.e., self-monitoring, intention formation, goal setting, goal review, and feedback) were embedded in intervention activities to maximize the effect of the intervention. Participants in the intervention group received a tailored behavioral weight loss curriculum via Facebook, smartphone applications, text-messages, blogs, e-mail, and health coach 'lifelines'. Participants were asked to interact with at least one intervention modality a minimum of five times per week.

3.2.4 Comparison Group

Participants assigned to the comparison group had access to a website without social networking components that contained general health information relevant to young adults (e.g., stress management, sexual-related health behavior, alcohol use). This website included some diet, PA, and sedentary behavior weight loss recommendations comparable to what individuals would receive from their primary care providers, but it did not include specific behavioral recommendations. Participants assigned to the comparison group were instructed to interact with at least one intervention modality weekly

3.2.5 Measures

Trained measurement staff who were blind to intervention randomization conducted physiologic measurements. They measured weight (kg) to the nearest 0.01-pound using a calibrated digital scale. Participants were asked to wear lightweight clothes (e.g., exercise clothes). Measurement staff weighed the participant twice and took the average of the two readings. They measured height using a stadiometer with the participant (without shoes) standing erect against the stadiometer rod. BMI was calculated from weight and height as kg/m^2.

Measurement staff also administered questionnaires to the participants. The following demographic information was collected: age, race/ethnicity, relationship status, education, and income. Categorical information was based on categories pre-defined by investigators. The 20-item SWM questionnaire assessed diet and PA weight management strategies commonly recommended in weight loss interventions. The SWM has good internal consistency (α = 0.89 for total score, α = 0.74 to 0.85 for the subscales), and subscales and total score predicted select concurrent, predictive, and construct relationships for diet and PA outcomes (J. Kolodziejczyk et al., under review). The SWM was adapted based on the validated Eating Behavior Inventory (EBI) and current weight-related behavioral strategies and recommendations[14,104]. The SWM is composed of four subscales: (1) energy intake, (2) energy expenditure, (3) self-monitoring, and (4) and self-regulation[105]. Participants were asked to select a response to each item based on their behavior from the "last 30 days". Each item on the SWM was rated on a five-point Likert scale (i.e., one = "hardly or never" and five = "always or almost always"). Items within each subscale are summed and divided by total items answered. Subscale scores range from 1 to 5. Subscale scores are summed to obtain a total score, and all subscale scores must be available to obtain a total score. Total scores range from 4 to 20. Measurement staff checked data from the questionnaires and were instructed to contact participants immediately to recover missing data (Table 3.1 and 3.2 indicate where there is missing data).

3.2.6 Statistical Analysis

Chi-Square Automation Interaction Detection (CHAID) is a signal detection method. CHAID uses chi-square tests to examine bivariate relationships between each predictor variable at each possible cut-point and the outcome variable[54]. Predictor variables are entered into the analysis simultaneously. The highest chi-square value of all variables at every possible cut-off point is designated as the 'best' test. The best test is set to maximize efficiency (i.e., it is set at the point where sensitivity and specificity are highest relative to each other). Data is split into two mutually exclusive and maximally discriminated subgroups at this designated cut point. The number of cut points for each variable equals one less than the number of categories (i.e., a dichotomous variable has one cut point). After splitting the data at this first cut point for the first predictor, the program searches each subgroup (i.e., nodes or branches) of the split for the next best predictor variable and cut point. Non-significant categories are merged. This splitting procedure continues until the number of subjects in a subgroup falls below a specified level, when no more significant variable cut points remain, or when no more predictor variables remain. CHAID was chosen for this analysis because, unlike other tree-based classification methods, it has the capability to merge non-significant categories and allows for multi-node splitting.

Signal detection was conducted to identify weight management strategies associated with weight loss success. The dichotomous outcome variable was yes/no ≥ 5% weight loss from baseline to 6 months (yes = ≥ 5% weight loss, no = < 5% weight loss). The target category was set to ≥ 5% weight loss. Predictor variables included SWM items, subscales, and total score at baseline and change scores from baseline to 6 months. SWM items were ordinal variables, and other SWM variables were continuous variables. Continuous variables were banded into discrete groups by intervals of two. Intervention group also was a predictor variable (intervention or comparison) and was a nominal variable.

The following settings were used in SPSS Statistics version 22 (SPSS Inc., Chicago, Illinois) to conduct CHAID[106]. The likelihood ratio for the chi-square statistic was used because it is more robust than Pearson. Re-splitting of merged categories was allowed. The significance level for split and merged categories was $p < 0.05$, and Bonferroni was used for multiple comparisons. Maximum tree depth was set at two; the minimum number of cases within each child node was set at 5% ($n = 19$), with parent nodes twice this size ($n = 38$)[107]; and number of iterations was set at 100. Misclassification costs were set to equal. For ordinal and continuous variables, the algorithms generate categories using valid values and decide whether to merge the missing category with its most similar category or keep it as a separate category. Missing values were included in the tree-growing process as a floating category that was allowed to merge with other categories in the tree nodes. To evaluate how well the tree structure generalizes to a larger population, cross-validation with 10 subsamples was conducted. In cross-validation, the full sample is compared to each subsample, and the misclassification risk for each tree model is calculated. The cross-validated risk estimate (i.e., the proportion of cases incorrectly classified) for the final tree (created from the full sample) is calculated by averaging the risk for all of the trees.

Subgroups identified with signal detection were displayed in a tree diagram. Chi-square statistics and percentages of participants were reported for each subgroup. Final subgroups were ordered by highest weight loss success.

A demographic profile of each final subgroup was provided to compare subgroups by demographic characteristics. One-way analysis of variance was conducted with continuous variables, and chi-square tests of independence were conducted with categorical variables. Continuous variables included age and BMI kg/m^2. Categorical variables included: (1) gender (male or female); (2) relationship status (single or in a committed relationship); (3) income (≤ $15,999, $16,000–$24,999, $25,000–$34,999, $35,000–$49,999, >$50,000, and "I don't know/I prefer not to answer"); (4) race/ethnicity; more than one race category could apply (yes/no Hispanic, yes/no white non-Hispanic, yes/no African-American, yes/no Asian, and yes/no other); and (5) education; graduate degree was included as a category even though one of the inclusion criteria was full-time enrollment in college because some students may be completing an additional degree (high school graduate/ General Educational Development (G.E.D.), education after high school, college graduate/Baccalaureate degree, or Master's/Doctoral degree). Categorical categories were collapsed if more than one cell had < 5 count.

3.3 Results

3.3.1 Descriptive Statistics

Table 3.1 and 3.2 show descriptive statistics for demographics and SWM scores, respectively. On average, participants were overweight, female, and single and had some education after high school and an income level of ≤ $15,999. Most participants were white non-Hispanic, followed by approximately equal percentages of Hispanic and Asian race/ethnicities. At baseline, subscale scores ranged from 1.7 (Self-monitoring) to 2.7 (Energy expenditure), and items ranged from 1.5 (Recorded and graphed my physical activity, Recorded and graphed my weight) to 3.0 (Exercised for a period of 30 minutes or more). Six-month change scores for subscales ranged from 0.1 (Energy expenditure) to 0.3 (Self-monitoring), and item scores ranged from 0.0 (Exercised at a gym or participated in an exercise class) to 0.7 (Recorded or wrote down the type and quantity of food eaten).

3.3.2 Signal Detection Results and Subgroup Profiles

Figure 1 shows the signal detection results in a tree diagram. A total of 15% (*n* = 57) of participants achieved ≥ 5% weight loss success. Change in SWM item #12 (“Recorded or graphed my weight”) was the first predictor variable among the full sample and divided the sample into those who reported a negative change/no change and those who reported a positive change (χ^2 (1, N = 381) = 15.0, adj. p < 0.001). The subgroup of participants who reported a positive change on SWM item #12 was further divided into those who scored ≤ 4 “Much of the time” or > 4 on SWM item #10 (“Exercised at a gym or participated in an exercise class”) at baseline (χ^2 (1, N = 158) = 7.0, adj. p = 0.03). Those who scored > 4 were in the first final subgroup, and those who scored ≤ 4 were in the second final subgroup. The subgroup of participants who reported a negative change/no change on SWM item #12 was divided further into those with a negative or positive change score on SWM item #7 (“Ate less fat”) (χ^2 (1, N = 223) = 5.7, adj. p = 0.02). Those with positive change were in the third final subgroup, and those with a negative change/no change were in the fourth final subgroup. The cross-validated risk estimate for the final tree was 0.16, SE = 0.02. For the four final subgroups identified in Figure 1, Table 3.3 shows the demographic profiles. There were no statistically significant difference between the demographic variables and the final subgroups.

3.4 Discussion

Three SWM items were found from this signal detection analysis that best predicted 5% weight loss success in overweight/obese young adults in a behavioral weight loss intervention study. These included change in recording or graphing weight, baseline score of exercising at a gym or participating in an exercise class, and change in eating less fat. The final subgroup with the highest likelihood of weight loss success included participants who reported a positive change in self-monitoring weight and a high baseline score of exercising at a gym or participating in an exercise class. Results from cross-validation indicate that 16% of the cases may have been incorrectly classified. This risk estimate suggests the final tree model has adequate predictive accuracy. Final subgroups identified did not differ by demographic characteristics. To date, this is the first study to apply signal detection methods to identify weight management strategies associated with 6-month weight loss among overweight/obese young adults participating in a weight loss intervention.

The variable that best predicted weight loss success was improvement in self-monitoring weight. Those who improved self-monitoring of weight had a higher likelihood of weight loss success than those who did not improve this behavior. This result is congruent with previous research showing consistent self-weighing increases weight loss success and maintenance (Burke et al., 2011; Butryn et al., 2007; Kruger et al., 2006; Linde et al., 2005), including among young adults (Gokee-Larose et al., 2009; Levitsky et al., 2006). These results suggest that researchers should consider monitoring change scores for this behavior throughout the intervention and targeting participants who are not improving.

The second best predictor of 5% weight loss success was baseline level of exercising at a gym or participating in an exercise class. The split occurred between those who scored ≤4 (“Much of the time”) and those who scored 5 (“Always or almost always”). Among those in the ≤4 group, most participants had a score of 1 (“Never or hardly ever”). This result is consistent with some previous research that showed access to a gym (Kapinos et al., 2013; Kapinos & Yakusheva, 2011; Quintiliani et al., 2012) and participating in group exercise classes (Gardner & Hausenblas, 2004) are factors that help increase physical levels and are related to weight management among young adults. The fact that baseline level was a strong predictor suggests that already having a gym/exercise class routine is helpful to achieve 5% weight loss, and the intervention may not have helped those without this routine improve their gym/exercise class behavior. This may be because barriers to increasing gym/exercise class behavior are difficult to overcome. For instance, gyms can be a source of psychological stress because of embarrassment caused by actual or anticipated negative evaluations from others (Ebben & Brudzynski, 2008; Vartanian & Shaprow, 2008). These feelings may prevent some individuals from engaging in exercise in public, particularly those who have never been to the gym or taken an exercise class (Nelson et al., 2009). Other important factors determining exercising at a gym for college students include access to a gym on campus, particularly a free, un-crowded, and convenient gym (Ebben & Brudzynski, 2008; Greaney et al., 2009), and time constraints from school and part-time jobs (D'Alonzo & Fischetti, 2008). Researchers should consider screening participants at baseline for this behavior and giving those with low scores tailored information on how to overcome these barriers.

Among those with a negative change/no change in self-monitoring weight, the next best predictor of 5% weight loss from baseline was change in fat intake. Those who reported that they reduced fat intake had a higher likelihood of weight loss success compared to those who did not. This result is consistent with previous research that has demonstrated that restricting fat intake is effective in creating an energy deficit that leads to weight loss (Frisch et al., 2009; Pirozzo et al., 2003; Sacks et al., 2009). Research has demonstrated the most effective low-fat approaches to weight loss among adults include reducing fat intake to 20%–40% of energy from fat (Jensen et al., 2013). The American Heart Association Step 1 diet for weight loss for adults includes limiting calories to 1,500–1,800 kcal/day, <30% of energy from fat, <7% of energy from saturated fat, <1% trans fat, and cholesterol to <300 mg/day (Krauss et al., 2000; Lichtenstein et al., 2006). These results suggest that a focus on reducing fat intake may improve weight loss success in this target population.

Results of the demographic profiles showed the final subgroups did not differ based on demographic characteristics. This result indicates that after tailoring intervention content to the three SWM items identified from this signal detection, there may not be a need to further tailor content based on the demographic characteristics assessed in this analysis when conducting an intervention involving a sample of young adult college students. Because of the relatively small sample size of the subgroups, these results should be interpreted with caution. Previous research involving young adults indicates that differences in weight behaviors exist among demographic groups. For instance, more female college students reported engaging in diet and exercise behaviors to lose weight than male college students (Aruguete et al., 2005; Wharton et al., 2011). This relationship also was found between white and black students, with white students reported higher engagement (Aruguete et al., 2005). However, these studies did not specify which diet and exercise strategies were used. Other research found that white college students were more likely to engage in higher levels of self-weighing than non-white students, but this study had a relatively small sample of non-white students (Mercurio & Rima, 2011). Results from research examining gender differences and PA is mixed. Some studies have found male college students have higher engagement in team sports or clubs and PA in general than female college students (Greene et al., 2011; Huang et al., 2003). Other studies found female college students use more PA-based weight management strategies to lose weight than male college students (Wharton et al., 2011), or no gender differences in PA (Racette et al., 2005). However, these studies did not specifically assess going to the gym or participating in exercise classes. With regard to fat intake, one study found young adult women of European descent had higher fat intake than African American women (Deshmukh-Taskar et al., 2007). In addition, researchers have reported male college students eat more fat (Morse & Driskell, 2009; Racette et al., 2005; Satia et al., 2004) and are less aware of the role of fat in weight loss than female college students (Davy et al., 2006). To date, no previous research has been conducted investigating the relationship between demographic characteristics and populations with the specific weight management characteristics identified in this signal detection.

This signal detection also provided evidence of predictive validity of the SWM. Evidence for this comes from the fact that distinct subgroups based on SWM items were identified that differed in clinically relevant weight loss. However, subscale scores and total score were not identified as predictive variables. This suggests individual SWM items are more predictive of weight loss success than subscale scores or total score for young adults.

Study limitations and strengths should be noted. Strengths include use of signal detection, as this method eliminates issues with multicollinearity and is a powerful method to detect interactions. Moreover, it is preferable to use signal detection when creating tailored interventions because this method identifies homogenous subgroups better than regression methods (Kiernan et al., 2001). A limitation of this study is it has limited external validity, as these findings are generalizable to only overweight/obese young adults enrolled in a behavioral weight loss intervention. Although these analyses tested the SWM in a diverse sample of young adults comprised of 68% ethnic minorities, the sample was mainly comprised of Hispanic and Asian minorities. Future research should conduct signal detection to investigate behavioral weight loss predictors with other populations, such as different age groups and race/ethnicities and individuals attempting weight loss on their own as opposed to those enrolled in a weight loss intervention. Another limitation is sample size. To construct a robust signal detection model, it is preferable to have node sizes between 75–100 participants (*IBM SPSS Decision Trees 20*, 2011). In this study, three of four nodes included >75 participants. Moreover, the sample had only 15% (n=57) of participants who achieved ≥5% weight loss. A larger portion of participants with successful weight loss may have identified more subgroups.

Researchers may use these results to emphasize the specific behavioral strategies that may be most helpful for the target group of overweight/obese young adults. The SWM can be used to screen participants at baseline for self-reported levels of exercising at a gym or participating in an exercise class and monitor change during the course of the intervention for self-monitoring weight and eating less fat. Information gathered from these SWM items can be used to target participants who may be at risk for <5% weight loss by individualizing intervention content to them. This approach to tailoring intervention content may increase the likelihood of achieving a clinically meaningful (>5%) amount of weight loss among young adults enrolled in weight loss interventions.

Acknowledgement: Chapter 3 is currently under review. The reference information is as follows: Julia K. Kolodziejczyk, Gregory J. Norman, Scott C. Roesch, Cheryl L. Rock, Elva M. Arredondo, Hala Madanat, and Kevin Patrick. Weight management strategies that predict the likelihood of weight loss among overweight/obese young adults using signal detection analysis. The co-authors have given her permission to use this manuscript for her dissertation.

APPENDIX 1: CHAPTER 1 TABLES

Table 1.1: Social Cognitive Theory Constructs Used to Inform the Development of the SWM

Construct	**SWM Sample Items**
Behavioral capacity	
• Knowledge	#10 Changed food preparation techniques
• Skill	#12 Followed a structured meal plan
Personal factors	
• Goal directed behavior via planning	#8 Decided ahead of time what I would eat for meals and snacks
• Self-efficacy via reducing perceived barriers	#4 Kept healthy ready-to-eat or portion controlled snacks for myself
• Self-efficacy via self-monitoring	#33 Recorded or graphed my physical activity
• Self-regulation	#6 If I was served too much, I left food on my plate
Environmental influences	
• Physical environment	#5 Removed high calorie foods from my home, office, or room
• Social Environment (social support)	#30 Exercised in a gym or participated in an exercise class

Table 1.2: Demographic Characteristics of the SMART (N=404) and ConTxt (N=236) participants

	Samples[1]		
	SMART[2]	**ConTxt**	**P**
Demographic Variables			
Age at study entry in years, mean (SD)	22.2 (3.8)	42.6 (11.1)	< 0.001***
BMI (kg/m^2), mean (SD)	29.0 (2.8)	32.4 (3.3)	< 0.01**
Female, N (%)	284 (70.3)	178 (75.4)	0.17
Education, N (%)			<0.001***
≤ High school graduate/G.E.D.	116 (28.7)	27 (11.4)	
Education after high school	206 (51.0)	86 (36.4)	
College graduate/Baccalaureate degree	62 (15.4)	58 (24.6)	
Master's/Doctoral degree	20 (5.0)	65 (27.5)	
Married, N (%)	31 (7.7)	103 (43.6)	<0.001***
Race/ethnicity, N (%)[3]			
Hispanic	125 (30.9)	60 (25.4)	0.15
White non-Hispanic	195 (48.3)	149 (63.1)	<0.001***
African American	20 (5.0)	78 (33.1)	<0.001
Asian	110 (27.2)	50 (21.2)	0.11
Other	21 (5.2)	11 (4.7)	0.85
Income, N (%)			<0.001***
≤ $15,999	275 (74.1)	34 (16.4)	
$16,000–$24,999	36 (9.7)	13 (6.3)	
$25,000–$34,999	34 (9.2)	31 (15.0)	
$35,000–$49,999	18 (4.9)	22 (18.4)	
$50,000–$74,999	1 (0.3)	38 (18.4)	
≥ $75,000	7 (1.9)	69 (33.3)	
"Don't know/Prefer not to answer"	23 (5.7)	29 (12.3)	

Notes:
*p<0.05, **p<0.01, ***p<0.001
[1]Percentages are rounded; therefore, some categories may not equal 100%
[2]Missing BMI, relationship status, Hispanic race data from one participant and missing income data from ten participants
[3]More than one race category could apply

Table 1.3: Four-Factor EFA and reliability results of the SWM items (N=404

Item	Parameter Estimates				Communality	α	Inter-Item r[1]
	Factor 1	Factor 2	Factor 3	Factor 4			
Factor 1 (Energy Intake)						0.85	0.41
16. Cut out/reduced sweets or junk food	0.93				0.73		(0.26–0.62)
18. Cut out/reduced late night snacking	0.71				0.51		
17. Cut out/reduced between meal snacks	0.70				0.47		
24. Decreased frequency or portion sizes of desserts	0.58				0.37		
15. Reduced my calorie intake	0.47				0.55		
5. Removed high calorie foods from my home, office or room	0.47				0.39		
20. Ate less fat	0.38				0.31		
22. Increased fruits and vegetables	0.38				0.27		
Factor 2 (Energy Expenditure)						0.83	0.61
32. Exercised for period of 30 minutes or more		-0.90			0.81		(0.53–0.74)
30. Exercised at a gym or participated in an exercise class		-0.81			0.67		
25. Altered my daily routine to get more lifestyle physical activity		-0.57			0.53		
Factor 3 (Self-Monitoring)						0.75	0.45
35. Recorded or graphed my weight			-0.94		0.78		(0.29–0.58)
33. Recorded or graphed my physical activity			-0.63		0.46		
13. Recorded or wrote down the type and quantity of food eaten			-0.58		0.41		
34. Weighed myself regularly or daily			-0.56		0.34		
Factor 4 (Self-Regulation)						0.77	0.34
6. If I was served too much, I left food on my plate				0.77	0.52		(0.19–0.63)
11. Left a few bites of food on my plate				0.73	0.49		
10. Changed food preparation techniques				0.54	0.44		
9. Reduced portion sizes				0.52	0.59		
8. Decided ahead of time what I would eat for meals and snacks				0.37	0.23		
2. Shopped from a list				0.36	0.18		
4. Kept healthy ready-to-eat or portion controlled snacks for myself				0.33	0.28		

Notes:
[1]Mean (range)

Table 1.4: Four-Factor CFA and reliability results of the SWM items (N=236)

Item	Parameter Estimates (Standard Error)				
	Factor 1	Factor 2	Factor 3	Factor 4	R^2
Factor 1 (Energy Intake)					
16. Cut out/reduced sweets or junk food	0.82(0.03)				0.67
18. Cut out/reduced late night snacking	0.55(0.05)				0.32
17. Cut out/reduced between meal snacks	0.68(0.04)				0.46
24. Decreased frequency or portion sizes of desserts	0.62(0.04)				0.39
15. Reduced my calorie intake	0.82(0.03)				0.68
5. Removed high calorie foods from my home, office or room	0.64(0.04)				0.41
20. Ate less fat	0.56(0.05)				0.31
22. Increased fruits and vegetables	0.52(0.05)				0.27
Factor 2 (Energy Expenditure)					
32. Exercised for period of 30 minutes or more		0.80(0.04)			0.64
30. Exercised at a gym or participated in an exercise class		0.63(0.05)			0.40
25. Altered my daily routine to get more lifestyle physical activity		0.82(0.04)			0.67
Factor 3 (Self-Monitoring)					
35. Recorded or graphed my weight			0.86(0.04)		0.74
33. Recorded or graphed my physical activity			0.55(0.05)		0.30
13. Recorded or wrote down the type and quantity of food eaten			0.56(0.05)		0.31
34. Weighed myself regularly or daily			0.57(0.05)		0.32
Factor 4 (Self-Regulation)					
6. If I was served too much, I left food on my plate				0.41(0.06)	0.17
10. Changed food preparation techniques				0.59(0.05)	0.35
9. Reduced portion sizes				0.77(0.04)	0.60
8. Decided ahead of time what I would eat for meals and snacks				0.58(0.05)	0.34
4. Kept healthy ready-to-eat or portion controlled snacks for myself				0.33(0.06)	0.11

Table 1.5: Descriptive Statistics of SWM Scores[1] from the SMART (N=404) and ConTxt (N=236) Participants

	Mean	**SD[2]**	**Median**	**Min**	**Max**
SWM Variables					
SMART					
Factor 1: Energy Intake	2.6	0.8	2.5	1.0	4.9
Factor 2: Energy Expenditure	2.7	1.1	2.3	1.0	5.0
Factor 3: Self-Monitoring	1.7	0.9	1.3	1.0	5.0
Factor 4: Self-Regulation	2.3	0.8	0.8	1.0	5.0
Total Score	9.2	2.7	8.9	4.2	18.3
ConTxt					
Factor 1: Energy Intake	2.6	0.9	2.6	1.0	5.0
Factor 2: Energy Expenditure	2.4	1.1	2.3	1.0	5.0
Factor 3: Self-Monitoring	1.7	0.8	1.5	1.0	5.0
Factor 4: Self-Regulation	2.5	0.8	2.4	1.0	5.0
Total Score	9.2	2.8	8.9	4.1	18.3

Notes:
[1]Factor scores range from 1–5, and total scores range from 4–20
[2]Standard deviation (SD)

Table 1.6: Linear Regression Models[1] Showing the Associations between SWM Scores and Demographic Variables of the SMART Participants (N=404)

Demographic Variables	Factor 2: Energy Expenditure	Factor 3: Self-Monitoring[2]	Factor 4: Self-Regulation[2]	Total Score[2]
Age	-0.04 (0.02) CI[3]:-0.07– -0.01, p=0.01**	0.00 (0.00) CI:-0.00–0.01, p=0.28	0.00 (0.00) CI:-0.00–0.01, p=0.15	
Education				
Gender				
Female	-0.30 (0.12) CI:-0.54– -0.06, p=0.01**		0.05 (0.02) CI:0.02–0.09, p=0.00***	
Male (reference)				
Relationship Status				
Married	-0.23 (0.22) CI:-0.66–0.20, p=0.30		0.04 (0.03) CI:-0.02–0.09, p=0.23	
Single (reference)				
Hispanic				
Yes		-0.06 (0.02) CI:-0.09– -0.12, p=0.01**		
No (reference)				
African American				
Yes				0.05 (0.03) CI:-0.00–0.11, p=0.06
No (reference)				
Goodness of Fit Statistics				
R^2	0.04	0.02	0.04	0.01
SS[3] Error	489.41	13.77	8.50	6.13
DF[4] Error	400	401	400	402

Notes:
*p < 0.05, **p > 0.01, ***p < 0.001
[1]Unstandardized parameter estimate (standard error); 95% confidence interval (CI) limits and p-value underneath
[2]Log-transformed variable
[3]Sum of squares (SS)
[4]Degrees of freedom (DF)

Table 1.7: Linear Regression Models[1] Showing the Associations between SWM Scores and Demographic Variables of the ConTxt Participants (N=236)

Demographic Variables	Factor 1: Energy Intake	Factor 2: Energy Expenditure[2]	Factor 3: Self-Monitoring[2]	Factor 4: Self-Regulation	Total Score[2]
Age	0.01 (0.01) CI:0.00–0.02, p=0.01**			0.01 (0.00) CI:0.00–0.02, p=0.01**	0.00 (0.00) CI:0.00–0.00, p=0.10
Education			0.00 (0.00) CI:0.00–0.00, p=0.07		
Gender					
Female				0.43 (0.12) CI:0.19–0.67, p=0.00***	
Male (reference)					
Relationship Status					
Married		-0.06 (0.03) CI:-0.11– -0.00, p=0.03*			
Single (reference)					
Other Race					
Yes				0.39 (0.25) CI:-0.09–0.88, p=0.11	
No (reference)					
Goodness of Fit Statistics					
R^2	0.03	0.02	0.02	0.08	0.01
SS[3] Error	186.81	9.41	7.82	146.53	3.91
DF[4] Error	234	234	234	232	234

Notes:
*p < 0.05, **p > 0.01, ***p < 0.001
[1]Unstandardized parameter estimate (standard error); 95% confidence interval (CI) limits and p-value underneath
[2]Log-transformed variable
[3]Sum of squares (SS)
[4]Degrees of freedom (DF)

APPENDIX 2: CHAPTER 2 TABLES

Table 2.1: Demographic Characteristics of the Study Participants (N=404)

	Sample[1,2]
Demographic Variables	
Age at study entry in years, mean (SD)[3]	22.2 (3.8)
BMI (kg/m^2), mean (SD)	29.0 (2.8)
Female, N (%)	284 (70.3)
Education, N (%)	
≤ High school graduate/G.E.D.	116 (28.7)
Education after high school	206 (51.0)
College graduate/Baccalaureate degree	62 (15.4)
Master's/Doctoral degree	20 (5.0)
Married, N (%)	31 (7.7)
Race/ethnicity, N (%)[4]	
Hispanic	125 (30.9)
White non-Hispanic	195 (48.3)
African American	20 (5.0)
Asian	110 (27.2)
Other	21 (5.2)
Income, N (%)	
≤ \$15,999	275 (74.1)
\$16,000–\$24,999	36 (9.7)
\$25,000–\$34,999	34 (9.2)
\$35,000–\$49,999	18 (4.9)
\$50,000–\$74,999	1 (0.3)
≥ \$75,000	7 (1.9)
"Don't know/Prefer not to answer"	23 (5.7)

Notes:
[1]Missing BMI, relationship status, Hispanic race data from one participant and missing income data from ten participants
[2]Percentages are rounded; therefore, some categories may not equal 100%
[3]Standard deviation (SD)
[4]More than one race category could apply

Table 2.2: Descriptive Statistics of Baseline and 6-month Strategies for SWM Scores, Weight, and Diet and PA Variables from the Study Participants

	Baseline				6-Months				Δ[1,2]	
Variables	**N**	**Mean**	**SD**[3]	**Range**	**N**	**Mean**	**SD**	**Range**	**Mean**	**P**
SWM Scores										
Energy Intake	404	2.6	0.8	1.0–4.9	378	2.9	0.9	1.0–5.0	0.3	0.001***
Energy Expenditure	404	2.7	1.1	1.0–5.0	376	2.8	1.1	1.0–5.0	0.1	0.02*
Self-Monitoring	404	1.7	0.9	1.0–5.0	377	2.1	1.0	1.0–5.0	0.4	0.001*** [3]
Self-Regulation	404	2.3	0.8	1.0–5.0	377	2.6	0.9	1.0–5.0	0.3	0.001***
Total Score		9.2	2.7	4.2–18.3	376	10.5	3.0	4.4–19.6	1.3	0.001***
Weight (kg)	404	81.1	12.9	54.8–119.0	381	80.5	13.1	53.1–124.2	-0.6	0.06
Diet Variables										
% Energy (Fat)	380	35.0	26.0	7.3–51.5	332	34.4	7.5	10.9–60.8	-0.6	0.33
% Whole Grains	380	15.1	11.1	0.0–78.3	332	14.9	10.7	0.0–73.8	-0.2	0.44[3]
Fruits (c)	380	1.2	1.2	0.0–9.4	332	1.2	1.0	0.0–7.0	0.0	0.18[3]
Vegetables (c)	380	1.6	1.1	0.2–6.9	332	1.5	1.2	0.2–8.6	-0.1	0.02*[3]
Discretionary Fat (g)	380	51.6	26.0	4.0–150.0	332	43.4	21.2	3.7–153.2	-8.2	0.001**[3]
Added Sugar (t)	380	11.1	10.3	1.5–113.9	332	9.6	9.1	0.7–65.1	-1.5	0.001**[3]
PA Variables										
Leisure PA (kcal/wk)	403	1,418.1	1,594.5	0.0–14,271.0	376	1,666.6	1,901.6	0–14,623.0	275.1	0.03*[3]
Leisure PA (min/wk)	403	232.1	252.6	0.0–2,780.9	376	256.5	280.6	0.0–2,520.0	24.4	0.20[3]

Notes:
*p< 0.5, **p< 0.01, ***p< 0.001
[1]Δ (change from baseline to 6-months)
[2]Paired-samples t-tests were used to assess mean differences between baseline and six-months for normally distributed data, and Wilcoxon signed rank test[3] was used for non-normal data
[3]Standard deviation (SD)
[4]Discretionary (disc.)

Table 2.3: Linear Regression Results[1] for the Evaluation of Concurrent Validity to Assess the Relationships between Baseline Weight and Diet and PA Variables on Baseline SWM Scores from the Study Participants

		SWM				
Dependent Variables	**N**	**Energy Intake**	**Energy Expenditure**	**Self-Monitoring**	**Self-Regulation**	**Total Score**
Weight	404	0.50 (2.12)	0.27 (0.49)	-0.06 (0.75)	-0.52 (0.70)	0.23 (0.24)
		-0.00, p=0.52	0.29, p=0.58	0.02, p=0.93	0.29, p=0.46	-0.00, p=0.92
Diet Variables	380					
% Energy from Fat		-1.28 (0.40)	-0.87 (0.30)	-0.77 (0.39)	-1.5 (0.43)	-0.47 (0.12)
		0.2, p<0.01**	0.01, p<0.01**	0.01, p=0.05	0.02, p<0.01**	0.03, p<0.001**
% Whole Grains[2]		0.25 (0.08)	0.27 (0.06)	0.15 (0.09)	0.40 (0.09)	0.12 (0.03)
		0.02, p<0.01**	0.06, p<0.001**	0.01, p=0.06	0.07, p<0.001**	0.05, p<0.001**
Fruits (c)[3]		0.09 (0.02)	0.06 (0.02)	0.03 (0.02)	0.05 (0.03)	0.03 (0.01)
		0.03, p<0.001**	0.03, p<0.01**	0.01, p=0.21	0.01, p=0.06	0.02, p<0.01**
Vegetables (c)[3]		0.02 (0.02)	0.01 (0.01)	0.00 (0.02)	-0.02 (0.02)	0.00 (0.01)
		0.01, p=0.24	0.06, p=0.65	0.04, p=0.99	0.06, p=0.34	0.01, p=0.62
Discretionary Fat (g)		-4.91 (1.62)	-0.59 (1.17)	-2.31 (1.58)	-6.46 (1.64)	-1.37 (0.50)
		0.02, p<0.01**	0.07, p=0.61	0.00, p=0.14	0.11, p<0.001**	0.01, p=0.01**
Added Sugar (t)[3]		-0.06 (0.02)	-0.01 (0.01)	-0.02 (0.02)	-0.02 (0.02)	-0.01 (0.01)
		0.02, p<0.01**	0.01, p=0.51	0.02, p=0.42	0.01, p=0.27	0.01, p=0.04*
PA Variables	403					
Leisure PA (kcal/wk)[2]		4.17 (1.09)	7.62 (0.72)	3.85 (1.05)	3.58 (1.13)	2.42 (0.32)
		0.03, p<0.001**	0.27, p<0.001**	0.05, p<0.001**	0.08, p<0.01**	0.12, p<0.001**
Leisure PA (min/wk)[1]		1.40 (0.42)	2.73 (0.28)	1.30 (0.41)	1.21 (0.44)	0.85 (0.13)
		0.03, p<0.01**	0.24 p<0.001**	0.04, p<0.01**	0.08, p<.01**	0.10, p<0.001**

Notes:
*p< 0.5, **p< 0.01, ***p< 0.001
[1]Unstandardized beta is reported with the standard error in parenthesis and adjusted R^2 and p-value underneath
[2]Square root transformed
[3]Log-transformed

Table 2.4: Linear[1] and Logistic Regression[2] Results for the Evaluation of Predictive Validity to Assess the Relationships between 6-Month Weight and Diet and PA Change Scores on SWM Baseline Scores from the Study Participants

				SWM		
Dependent Variables	N	Energy Intake	Energy Expenditure[3]	Self-Monitoring[3]	Self-Regulation[3]	Total Score
% Weight Loss	381	-0.42 (0.30)	-0.62 (0.22)	-0.19 (0.28)	-0.48 (0.31)	-0.20 (0.09)
		0.00, p=0.15	0.03, p=0.01*	0.01, p=0.49	0.01, p=0.13	0.01, p=0.03*
Diet Variables	320					
Δ % Energy from Fat		0.09 (0.53)	0.01 (0.38)	-0.37 (0.52)	-0.38 (0.57)	-0.06 (0.17)
		-0.00, p=0.87	-0.01, p=0.98	-0.00, p=0.47	-0.01, p=0.50	-0.01, p=0.74
Δ % Whole Grains		1.26 (0.96–1.67)	0.99 (0.81–1.22)	1.18 (0.90–1.53)	1.16 (0.87–1.54)	1.06 (0.97–1.15)
		p=0.10	p=0.95	p=0.23	p=0.33	p=0.19
Δ Fruits (c)		0.88 (0.67–1.16)	0.96 (0.78–1.17)	1.11 (0.85–1.45)	1.16 (0.87–1.55)	1.00 (0.92–1.09)
		p=0.36	p=0.69	p=0.43	p=0.30	p=0.92
Δ Vegetables (c)		-0.06 (0.08)	0.03 (0.06)	0.13 (0.08)	0.02 (0.08)	0.01 (0.03)
		-0.00, p=0.42	0.00, p=0.58	0.00, p=0.09	0.00, p=0.85	0.01, p=0.72
Δ Discretionary Fat (g)		0.87 (1.65)	-1.12 (1.21)	0.04 (1.60)	1.65 (1.72)	0.03 (0.51)
		0.00, p=0.60	0.03, p=0.35	0.00, p=0.98	0.03, p=0.34	-0.01, p=0.96
Δ Added Sugar (t)		1.34 (1.01–1.77)	1.07 (0.87–1.32)	1.25 (0.96–1.64)	1.19 (0.89–1.60)	1.07 (0.98–1.17)
		p=0.04*	p=0.51	p=0.10	p=0.24	p=0.11
PA Variables	375					
Δ Leisure PA (kcal/wk)		1.19 (0.93–1.53)	0.86 (0.71–1.03)	0.94 (0.74–1.19)	1.02 (0.79–1.32)	1.00 (0.92–1.08)
		p=0.17	p=0.10	p=0.59	p=0.88	p=0.96
Δ Leisure PA (min/wk)		1.20 (0.94–1.53)	0.85 (0.70–1.02)	0.94 (0.74–1.20)	1.02 (0.79–1.32)	1.00 (0.92–1.08)
		p=0.15	p=0.09	p=0.64	p=0.89	p=0.94

Notes:
*p< 0.05, **p< 0.01, ***p< 0.001
[1]For linear regressions, unstandardized beta is reported with the standard error in parenthesis and adjusted R^2 and p-value underneath
[2]For logistic regressions, the odds ratio is reported with the 95% confidence interval in parenthesis and p-value underneath (negative change was coded as 0, positive change was coded as 1)
[3]Missing data from one participant
[4]Δ (change from baseline to 6-months)

Table 2.5: Linear Regression[1] Results for the Evaluation of Construct I Validity to Assess the Relationships Between the Study Participants' 6-Month SWM Change Scores on Treatment Group (N=378)

	SWM Change From Baseline to 6-Months				
Independent Variable	Δ Energy Intake	Δ Energy Expenditure	Δ Self-Monitoring	Δ Self-Regulation	Δ Total Score
	N=378	N=376	N=377	N=377	N=376
Treatment	0.21 (0.09)	0.06 (0.13)	0.50 (0.10)	0.11 (0.09)	0.84 (0.30)
	0.03, p=0.01*	-0.01, p=0.64	0.06, p<0.001**	0.00, p=0.20	0.03, p=0.01*
Control (reference)					

Notes:
*p< 0.05, **p< 0.01, ***p< 0.001
[1]Unstandardized beta is reported with the standard error in parenthesis and adjusted R^2 and p-value underneath

Table 2.6: Linear[1] and Logistic[2] Regression Results for the Evaluation of Construct II Validity to Assess the Relationship Between 6-Month Weight and Diet and PA Change Scores on 6-Month SWM Change Scores from the Study Participants

		SWM Change From Baseline to 6-Months				
Dependent Variables	N	Δ Energy Intake	Δ Energy Expenditure	Δ Self-Monitoring	Δ Self-Regulation	Δ Total Score
% Weight Loss	376	-0.95 (0.26)	-0.27 (0.20)	-1.21 (0.24)	-1.15 (0.30)	-0.39 (0.08)
		0.03, p<0.001**	0.02, p=0.17[3]	0.07, p<0.001**[4]	0.05, p<0.001**[5]	0.05, p<0.001**[5]
Diet Variables	316					
Δ % Energy from Fat		-0.56 (0.48)	0.09 (0.35)	-0.20 (0.46)	-0.03 (0.55)	-0.08 (0.16)
		0.00, p=0.25	-0.01, p=0.81[5]	0.00, p=0.67[4]	-0.11, p=0.96[5]	-0.01, p=0.60[4]
Δ Whole Grains		0.77 (0.60–0.99)	0.93 (0.78–1.10)	1.10 (0.87–1.39)	0.81 (0.61–1.08)	0.95 (0.87–1.02)
		p=0.04*	p=0.38[5]	p=0.42[4]	p=0.14[5]	p=0.17[4]
Δ Fruits (c)		1.22 (0.95–1.56)	1.13 (0.95–1.35)	1.13 (0.90–1.43)	0.87 (0.65–1.15)	1.05 (0.97–1.14)
		p=0.12	p=0.18[5]	p=0.29[4]	p=0.31[5]	p=0.22[4]
Δ Vegetables (c)		0.23 (0.07)	0.03 (0.05)	0.03 (0.07)	0.02 (0.08)	0.04 (0.02)
		0.03, p<0.01*	0.00, p=0.59[5]	-0.01, p=0.63[4]	0.00, p=0.79[5]	0.02, p=0.07[4]
Δ Discretionary Fat (g)		-2.73 (1.49)	0.64 (1.05)	0.41 (1.41)	-4.81 (1.65)	-0.51 (0.48)
		0.01, p=0.07	0.03, p=0.54	0.00, p=0.98	0.05, p<0.01**	-0.00, p=0.28
Δ Added Sugar (t)		0.58 (0.44–0.76)	0.91 (0.76–1.09)	0.87 (0.68–1.10)	0.54 (0.39–0.74)	0.87 (0.80–0.95)
		p<0.001**	p=0.31[5]	p=0.25[4]	p<0.001**[5]	p<0.001**[4]
PA Variables	373					
Δ Leisure PA (kcal/wk)		1.47 (1.16–1.85)	1.74 (1.43–2.11)	1.57 (1.26–1.97)	1.67 (1.27–2.18)	1.27 (1.17–1.38)
		p<0.01**	p<0.001**[5]	p<0.001**	p<0.001**[4]	p<0.001**[4]
Δ Leisure PA (min/wk)		1.36 (1.08–1.71)	1.74 (1.43–2.11)	1.65 (1.31–2.07)	1.68 (1.28–2.20)	1.26 (1.16–1.37)
		p<0.001**	p<0.001**[5]	p<0.001**	p<0.001**[4]	p<0.001**[4]

Notes:
*p< 0.05, **p< 0.01, ***p< 0.001
[1]For linear regressions, unstandardized beta is reported with the standard error in parenthesis and adjusted R^2 and p-value underneath.
[2]For logistic regressions, the odds ratio is reported with the 95% confidence interval in parenthesis and p-value underneath (negative change was coded as 0, positive change was coded as 1).
[3]Missing data from three participants
[4]Missing data from one participant
[5]Missing data from two participants

Table 2.7: Summary Percentages by SWM Score and Validity Type

SWM	Validity[1]		
	Concurrent	**Predictive**	**Construct II**
Energy Intake	71% (5 of 7)	14% (1 of 7)	43% (3 of 7)
Energy Expenditure	67% (2 of 3)	33% (1 of 3)	67% (2 of 3)
Self-Monitoring	22% (2 of 9)	0% (0 of 9)	33% (3 of 9)
Self-Regulation	43% (2 of 7)	0% (0 of 7)	43% (3 of 7)
Total Score	78% (7 of 9)	11% (1 of 9)	44% (4 of 9)
		Divergent Validity[2]	
Energy Intake	0% (0 of 2)	100% (2 of 2)	0% (0 of 2)
Energy Expenditure	50% (3 of 6)	100% (6 of 6)	100% (6 of 6)
Self-Regulation	0% (0 of 2)	100% (2 of 2)	0% (0 of 2)

Notes:
[1]Construct I validity is not listed in this table because the SWM factors and total score comprise only one regression result (treatment vs. the reference control group)

APPENDIX 3: CHAPTER 3 TABLES

Table 3.1: Descriptive Statistics of Demographic Variables Used in the Signal Detection Analysis (N=404)

Demographic Variables	**Sample[1,2]**
Age at baseline in years, mean (SD)[3]	22.2 (3.8)
BMI at baseline (kg/m^2), mean (SD)	29.0 (2.8)
Female, N (%)	284 (70.3)
Education, N (%)	
High school graduate/G.E.D.	116 (28.7)
Education after high school	206 (51.0)
≥Baccalaureate degree	82 (20.3)
Single, N (%)	232 (57.3)
Race/ethnicity, N (%)[4]	
Hispanic	125 (30.9)
White non-Hispanic	195 (48.3)
African American	20 (5.0)
Asian	110 (27.2)
Other	21 (5.2)
Income, N (%)	
≤ $15,999	275 (69.8)
$16,000–$24,999	36 (9.1)
$25,000–$34,999	34 (8.6)
$35,000–$49,999	18 (4.6)
≥$50,000	8 (2.0)
"Don't know/Prefer not to answer"	23 (5.8)

Notes:
[1]Missing BMI, relationship status, Hispanic race data from one participant and missing income data from ten participants
[2]Percentages are rounded; therefore, some categories may not equal 100%
[3]Standard deviation (SD)
[4]More than one race category could apply

Table 3.2: Descriptive Statistics of Baseline and 6-month Change Scores for the Strategies for Weight Management Items, Subscales, and Total Score Used in the Signal Detection Analysis

Variables	Baseline			6-Month Change		
	N	Mean	SD	N	Mean	SD
Subscale 1: Energy Intake	404	2.6	0.8	378	0.3	0.9
Item #1 Cut out/reduced sweets or junk food	403	2.8	1.2	376	0.2	1.4
Item #2 Cut out/reduced late night snacking	401	2.6	1.3	375	0.3	1.5
Item #3 Cut out/reduced between meal snacks	402	2.4	1.2	376	0.3	1.4
Item #4 Decreased frequency or portion sizes of desserts	403	2.8	1.3	375	0.1	1.5
Item #5 Reduced my calorie intake	403	2.3	1.1	377	0.4	1.3
Item #6 Removed high calorie foods from my home, office or room	404	2.2	1.3	375	0.4	1.4
Item #7 Ate less fat	404	2.6	1.1	377	0.3	1.2
Item #8 Increased fruits and vegetables	404	3.0	1.1	377	0.3	1.3
Subscale 2: Energy Expenditure	404	2.7	1.1	376	0.1	1.3
Item #9 Exercised for period of 30 minutes or more	403	3.0	1.3	374	0.2	1.5
Item #10 Exercised at a gym or participated in an exercise class	403	2.6	1.4	374	0.0	1.5
Item #11 Altered my daily routine to get more lifestyle physical activity	404	2.5	1.1	375	0.3	1.5
Subscale 3: Self-Monitoring	404	1.7	0.9	377	0.5	1.0
Item #12 Recorded or graphed my weight	403	1.5	1.0	376	0.3	1.3
Item #13 Recorded or graphed my physical activity	404	1.5	1.0	377	0.3	1.2
Item #14 Recorded or wrote down the type and quantity of food eaten	403	1.6	1.0	375	0.7	1.6
Item #15 Weighed myself regularly or daily	403	2.1	1.4	374	0.6	1.5
Subscale 4: Self-Regulation	404	2.3	0.8	377	0.3	0.8
Item #16 If I was served too much, I left food on my plate	404	2.1	1.1	376	0.3	1.2
Item #17 Changed food preparation techniques	403	2.1	1.1	374	0.3	1.3
Item #18 Reduced portion sizes	404	2.4	1.1	377	0.5	1.2
Item #19 Decided ahead of time what I would eat for meals and snacks	404	2.9	1.2	376	0.1	1.3
Item #20 Kept healthy ready-to-eat or portion controlled snacks for myself	403	2.1	1.2	376	0.3	1.5
Total Score	404	9.2	2.7	376	1.2	2.9

Notes:
[1]Standard deviation (SD)

Table 3.3: Demographic Characteristic Profiles of the Four Final Subgroups Identified by Signal Detection Analysis (N=381)[1]

Variables	Subgroup 1	Subgroup 2	Subgroup 3	Subgroup 4	P	Effect Size
Continuous Variables						$\eta^{2\,(3)}$
Age, mean (SD)[2]	21.15±3.0	22.23±3.6	21.77±3.4	22.56±4.2	0.22	0.01
BMI-baseline (kg/m^2), mean (SD)	29.62±3.0	29.01±2.7	28.3±2.6	29.2±2.8	0.06	0.02
Categorical Variables						Φ^4
Female (%)	63.0% (n=17)	72.7% (n=112)	70.5% (n=55)	69.0% (n=100)	0.74	0.06
Baccalaureate degree (%)	22.2% (n=6)	20.1% (n=31)	15.4% (n=12)	22.8% (n=33)	0.62	0.16
Single (%)	55.6% (n=15)	52.6% (n=81)	68.8% (n=53)	57.2% (n=83)	0.13	0.12
Race/ethnicity (%)						
Hispanic	22.2% (n=6)	31.4% (n=48)	35.9% (n=28)	29.7% (n=43)	0.58	0.07
White non-Hispanic	55.6% (n=15)	49.4% (n=76)	50.0% (n=39)	44.8% (n=65)	0.70	0.06
Asian	25.9% (n=7)	28.6% (n=44)	25.6% (n=20)	26.9% (n=39)	0.97	0.03
Other	14.8% (n=4)	6.5% (n=10)	11.5% (n=9)	35.9% (n=145)	0.34	0.04
≤$15,999 income	75.0% (n=18)	71.5% (n=103)	82.4% (n=61)	72.1% (n=93)	0.33	0.10

Notes:

[1]One-way ANOVAs were used with continuous variables and chi-square tests for independence were used with categorical variables. Values are expressed as mean±SD unless otherwise noted

[2]Standard deviation (SD)

[3]Eta squared (η^2)

[4]Phi coefficient (Φ)

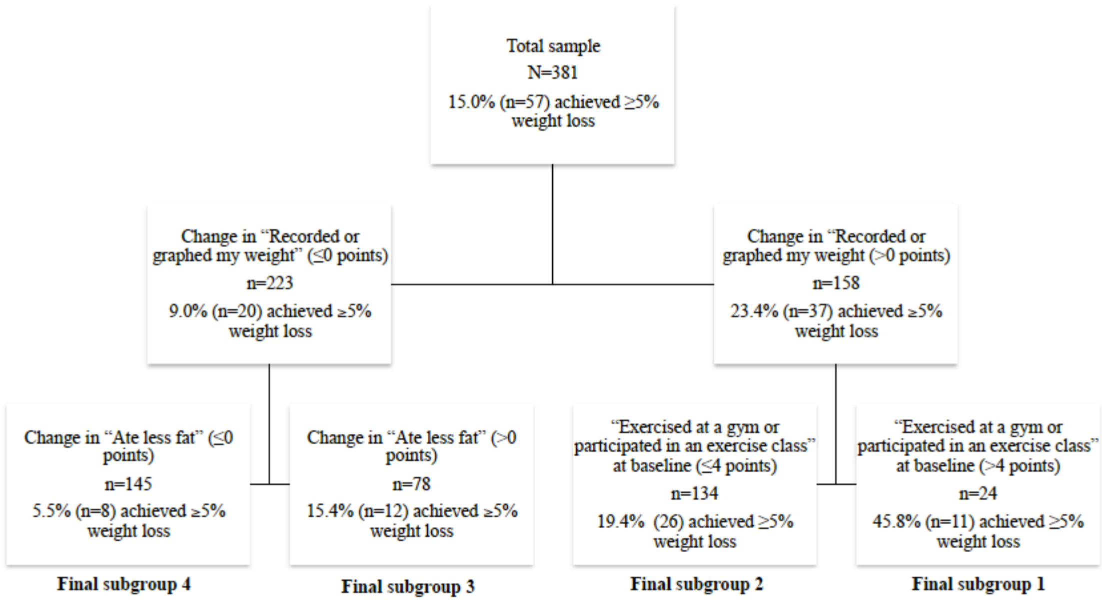

Figure 3.1: Signal Detection Tree Diagram. This figure illustrates the final subgroups identified by signal detection analysis ordered by weight loss success.

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