Brief Communication

DIGITAL HEALTH

Digital Health
Volume 6: 1–7

DOI: 10.1177/2055207620976755
journals.sagepub.com/home/dhj
SAGE

The role of self-efficacy and information processing in weight loss during an mHealth behavioral intervention

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Abstract

Self-efficacy (SE) and information processing (IP) may be important constructs to target when designing mHealth interventions for weight loss. The goal of this study was to examine the relationship between SE and IP with weight loss at six-months as part of the Dietary Interventions Examining Tracking with mobile study, a six-month randomized trial with content delivered remotely via twice-weekly podcasts. Participants were randomized to self-monitor their diet with either a mobile app ($n = 42$) or wearable Bite Counter device ($n = 39$). SE was assessed using the Weight Efficacy Life-Style Questionnaire and the IP variables assessed included user control, cognitive load, novelty, elaboration. Regression analysis examined the relationship between weight loss, SE change & IP at six months. Results indicate that elaboration was the strongest predictor of weight loss ($ß = -0.423$, $P = 0.011$) among all SE & IP variables and that for every point increase in elaboration, participants lost 0.34 kg body weight.

Keywords

Weight loss, mobile health, technology, diet, dietary self-monitoring

Submission date: 2 October 2019; Acceptance date: 2 November 2020

Introduction

Remotely-delivered mobile health (mHealth) weight loss interventions have the potential to translate evidence-based face-to-face behavioral interventions into a more scalable form.[1] Content, theoretical constructs, and delivery methods used in previous interventions have varied widely across studies.[1] In order to guide the design of effective mHealth interventions, it is important to examine the theoretical drivers of weight loss during mHealth weight loss interventions.

Self-efficacy is an important construct of Social Cognitive Theory (SCT) and is one theoretical driver of weight loss that has been examined in numerous previous weight loss studies.[2] The relationship between self-efficacy and weight loss has been mixed, with some studies finding self-efficacy to be a predictor of successful weight loss[3] and other studies not finding a relationship.[4] In addition, few studies have examined the relationship between self-efficacy and weight loss during entirely remotely delivered interventions.

Because mHealth interventions rely on digital media to communicate information, it may also be important

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to consider communication and information processing variables to target during intervention development. Some communication and information processing theories relevant to learning behavior change via mHealth media include User Control Theory,[5] Cognitive Load Theory,[6] and the Elaboration Likelihood Model (ELM).[7] User Control Theory states that an increase in the variety of different ways to learn and access information adds to the control a user feels and therefore increases learning.[5] Cognitive Load Theory states that the more cognitive burden, or mental effort, users feel when learning, the less able they will be to retain and act upon what they learned.[6] A common barrier to continued use of mHealth apps is the feeling of excess message overload.[8] The Elaboration Likelihood Model (ELM) states that a recipient receives information, evaluates it, and then forms a decision about how that information will be used.[7] Elaboration refers to how deeply someone is processing the information. In addition, the ELM states that individuals will actively process information more deeply when it is deemed personally relevant to them and that deeper processing leads to greater changes in attitude and behavior than if the information is considered unimportant.[9] Therefore, increasing elaboration can lead to greater thoughtfulness of informational messages, leading to persuasion to arguments presented in those messages.[10] Lastly, novelty may play a role in reinforcement learning and reward processing,[11] which could in turn improve adherence and engagement in mHealth interventions. Studying the interplay of information processing and self-efficacy-related variables may allow for a better understanding of which variables are most likely to lead to behavior change, and therefore should be the target of future intervention development. A previous study, in fact, found information processing variables mediated the relationship between an mHealth intervention and weight loss, but SCT variables, such as self-efficacy, did not.[4]

The Dietary Intervention to Enhance Tracking with mobile (DIETm) study was a six-month randomized weight loss trial that was entirely remotely-delivered.[12] Content was delivered by audio podcasts and participants were randomized to self-monitor their diet either via a traditional calorie tracking app or a wrist-worn device, called the Bite Counter, which tracked eating frequency via bites. Because the DIETm study, which was designed using SCT, examined both self-efficacy and information processing variables (elaboration, user control, cognitive load, and novelty), it provides a unique opportunity to examine the relationship of these potential theoretical drivers of behavior change and weight loss. The goal of this paper is to examine the relationship of self-efficacy change and information processing with weight loss at six-months. Six-month outcomes in both weight and constructs of self-efficacy and information processing were examined in order to allow participants the entire time to obtain the information provided in the podcasts and adequate time to become familiar with their dietary self-monitoring method. We hypothesized that information processing variables would have a stronger association with weight loss than self-efficacy, but that both would be positively related to weight loss outcomes.

Methods

Methods of dietary self-monitoring and inclusion/exclusion criteria for DIETm have been described elsewhere.[12] Briefly, participants (adults with a BMI 25-49.9 kg/m^2, owned an Android phone or iPhone, between the ages of 18-65 years) were randomized to self-monitor their diet with either a mobile app (App, n = 42) or wearable Bite Counter device (Bite, n = 39). The Bite Counter, which has been shown to accurately detect bites with a sensitivity of 75% and a positive predictive value of 89%,[13] is a wrist-worn device that monitors dietary intake by counting bites through the use of a micro-electro-mechanical gyroscope (http://icountbites.com/). Methods of determining energy intake from the Bite Counter have been described elsewhere.[14,15] The App group was instructed to track kcals/day on their app (FatSecret). The Bite group was told to track bites/day (which corresponded to a similar kcals/day limit) on their device. Both groups received the same behavioral weight loss information via twice-weekly podcasts, which were informed by SCT. The University of South Carolina's Institutional Review Board approved the study and informed consent was obtained from all individual participants included in the study.

Self-efficacy was assessed at baseline and then again at six months using the validated Weight Efficacy Life-Style Questionnaire (WEL).[16] The WEL consists of 20 items and assesses five situational factors related to weight control: Negative Emotions, Availability, Social Pressure, Physical Discomfort, and Positive Activities. All items from the WEL were tallied together (summed) to create a single composite score. Each participant's change in self-efficacy was computed as six-month composite score minus baseline composite score. Participants answered additional questions on a 7-point Likert scale that assessed user control (3 questions; range 3 to 21 representing highest user control or freedom in participating in the mHealth intervention),[5] cognitive load (2 questions; range 2 to 14 representing lowest cognitive load or degree of cognitive burden during the mHealth intervention), and novelty (2 questions; range 2 to 14 representing highest perceived novelty or how innovative participating in the intervention was). Elaboration was assessed using the 9-item ELM

Table 1. How intervention components targeted each theoretical construct and example survey items assessing each construct.

	Targeted intervention component	Example survey items
Information processing variables:		
Elaboration	Podcasts targeted central route processing by targeting a sense of personal relevance (asking participants to reflect on personal motivations for weight loss) and focusing on one topic at a time (reducing distractions) and repeating important messages.	How motivated were you to obtain the information from this weight loss intervention? How much would you say the information from this weight loss intervention held your attention?
User control	Podcasts are divided into 4 sections within each episode to allow for easy navigation. Participants are trained on how to use their dietary self-monitoring device.	I felt like I was able to learn at a good pace during this study.
Novelty	Recruited participants who are are novices at both weight loss podcast usage and dietary self-monitoring with FatSecret or the Bite Counter.	I found this weight loss intervention to be very new and innovative.
Cognitive Load	Podcast scripts are written for basic understanding and provide an overview at the beginning to lessen mental effort.	How much mental effort did you have to spend when getting the information for this study?
Self-efficacy (WEL-Q questionnaire)	Negative emotions: Podcast audio blogs provided scenarios where the author demonstrated how they resisted eating when feeling a negative emotion.	I can resist eating when I am anxious (nervous).
	Availability: Topics in the podcast provided strategies for avoiding eating when palatable food was around (e.g., hide treats in the back of a cabinet).	I can resist eating even when I am at a party.
	Social pressure: Podcast audio blogs provided scenarios where the author demonstrated how they resisted eating when at a social gathering.	I can resist eating even when I have to say "no" to others.
	Physical discomfort: Topics in the podcast provided strategies for avoiding eating when you have a headache or feel tired.	I can resist eating when I feel physically run down.
	Positive activities: Topics in the podcast provided strategies for avoiding eating when doing mindless activities, like being on the computer or watching TV.	I can resist eating when I am reading.

questionnaire slightly modified for this study. Table 1[17] provides example survey items for each construct assessed. These measures have been used in previous work.[4] Height (stadiometer (SECA 213)) and weight (SECA 869, Hamburg, Germany) were measured by trained assessors who were blinded to study condition. Table 1 provides details on how the intervention components targeted each of the information processing or self-efficacy constructs.

Statistical analysis

Power calculations for the main analysis are described elsewhere.[12] For the present study, our minimum detectable standardized beta with a sample size of 81 is 0.30, which represents a medium effect size. To examine differences in baseline characteristics between those with and without complete data at six months, independent samples t tests were used for continuous variables and chi-square test of independence was used for categorical data. Weight loss was the primary outcome. Among sociodemographic variables, only sex and age had sufficient variability and degree of association with weight loss to act as covariates. Therefore, sex and age are included along with treatment group as covariates in the model as covariates.

SAS statistical software (SAS Institute Inc., Version 9.4) was used for data management and descriptive statistics. Mplus Version 8.2 was used for multiple imputation and regression modeling. Because there was greater than 25% attrition from baseline to six months for both weight and questionnaire data, analyzing only the complete cases would be inappropriate. Therefore, a multiple imputation procedure was used to create 40 replicates of a dataset with missing six-month values of weight loss and all information processing and SCT variables imputed. All available information in the dataset (baseline, 3-month and 6-month weights, baseline and 6-month SE, 6-month IP, and baseline covariates) was used to perform the imputation. Under a Missing at Random (MAR) assumption, regression analysis on the multiple imputed datasets provides unbiased estimates and robust standard errors for regression parameters. The Mplus unrestricted (H1) modeling technique was used for multiple imputation.

A Latent Change Score (LCS) regression approach allows full utilization of the available information on change in body weight and SE as well as single measures of IP constructs and covariates including treatment group. Specifically, an ANCOVA model formulation within the LCS framework was used as recommended by Valente and MacKinnon.[18] These models also allow examination of potential mediators of treatment effects, but no mediation was present in this study. Independent variables were the latent variable for SE change and manifest variables for IP constructs and covariates with the outcome being a latent weight change score.

Results

Main outcomes of the DIETm study have been presented elsewhere.[12] Briefly, examining both groups combined, participants lost significant weight (mean± SD) at six months (-4.9 ± 5.9 kg; $p < 0.001$). For the present study, both App and Bite groups were combined ($n = 81$). Attrition at six months was 25% for main outcome of weight loss, 34% for questionnaire data (self-efficacy and information processing variables), and 36% for both weight and questionnaire data at six months. Baseline characteristics of those who completed all measures in the study ($n = 52$) were similar to those who did not ($n = 29$) with no significant differences (Table 2).

Self-efficacy increased significantly over the course of the study (baseline 112.8 ± 29.6, 6 months 133.0 ± 31.1; change $+20.2 \pm 28.0$ points, $p < 0.001$) and was modeled as a latent change score. Information processing variables could only be assessed at six months. Table 3 provides the outcomes of the treatment-, age-, and sex-adjusted models that examined six-month scores on the information processing variables and change scores for self-efficacy regressed on the outcome of weight loss at 6 months (R^2=0.425, $P < 0.001$). Prior to constructing a multivariable weight loss model, unadjusted bivariate correlations of each variable with weight loss were computed. Unadjusted bivariate correlations of weight loss with elaboration (-0.411) as well as the covariate sex (0.293) were statistically significant when examining each variable individually.

In the model examining the four information processing constructs as well as change in self-efficacy, adjusted for group, sex and age, only elaboration emerged as a significant predictor of weight loss ($ß = -0.423$, $P = 0.011$). Results indicate that elaboration was the strongest predictor of weight loss among all self-efficacy and information processing variables that were examined and that higher levels of elaboration are associated with more weight loss (e.g., each point higher in the elaboration score was associated with a 0.34 kg decrease in body weight). Among the covariates, sex and treatment group were statistically significant in the multivariable model.

Discussion

Remotely delivered interventions are scalable ways to reach large numbers of people. In addition, digital interventions can overcome many of the barriers commonly seen with in-person interventions, such as lack of transportation or childcare.[19] Developing mHealth interventions can be cost- and time-intensive, so knowing the important theoretical drivers of behavior change can help streamline future development of mHealth interventions, potentially reducing both time and cost investments and focusing resources on aspects known to help produce behavior change.

The findings of this study point to elaboration, or how deeply someone is thinking about the issues being presented, being the primary variable associated with weight loss. Previous research has also found elaboration to be an important component of mHealth usage. For example, one study found that perceived usefulness of a health app, trust in the app, and the app's reputation were all were important factors for increasing elaboration, leading to sustained use of the app.[20] In addition, a previous study found information processing variables (e.g., cognitive load, elaboration, user control) mediated the relationship between a podcasting intervention and weight loss, but self-efficacy, did not.[4] In the present study, while similar results were found for social cognitive variables, only elaboration emerged as an important predictor for information processing variables. It is possible that within the past decade (since the previous study was conducted), users have become more familiar with technology, lessening the need to focus on user control and cognitive load.

Table 2. Baseline demographics of participants in the DIET Mobile remotely-delivered weight loss interventions.

	Entire sample	Participants with complete data at six months	Participants with missing data (weight and/or questionnaires) at six months	P-value for difference between those with complete and incomplete data
n	81	52	29	
Mean age (±SD)	48.1 ± 11.9	49.6 ± 11.5	45.4 ± 12.2	0.13
Sex (n, (%))				0.55
Female	67 (83%)	44 (85%)	23 (79%)	
Male	14 (17%)	8 (15%)	6 (21%)	
Race (n, (%))				0.40
Black or other	14 (17%)	9 (17%)	6 (21%)	
White	66 (82%)	43 (83%)	23 (79%)	
Education (n, (%))				0.59
High school or some college	12 (15%)	6 (21%)	6 (12%)	
College graduate	37 (46%)	14 (48%)	23 (44%)	
Advanced degree	32 (39%)	9 (31%)	23 (44%)	
Marital Status (n, (%))				0.84
Married	50 (62%)	32 (61%)	18 (62%)	
Partnered/Living with someone	5 (6%)	3 (6%)	2 (7%)	
Single	20 (25%)	14 (27%)	6 (21%)	
Divorced	6 (7%)	3 (6%)	3 (10%)	
Mean BMI (kg/m^2) (±SD)	34.7 ± 5.6	34.8 ± 5.7	34.6 ± 5.5	0.87

The concept of elaboration differs from some other standard behavioral theory constructs in that it does not specify constructs or ways to drive behavior change. Therefore, it is possible that focusing on ways to ensure high levels of user control, novelty, and self-efficacy, and low levels of cognitive load in mHealth interventions can all result in greater elaboration and these may still be important constructs to target in the design of the intervention. Some examples of mHealth design elements that could target user control, cognitive load, and novelty, while increasing elaboration, include increasing the flexibility of delivery methods and personalization of intervention components, making instructions for use very simple and easy to understand, building in information filtering components, such as recommender systems, that allow for prioritization of information, or providing new and varied ways to enter personal health information. Ways to increase self-efficacy that could also potentially target elaboration include providing instruction and reinforcement of successful behavior change and building in opportunities for vicarious experience via observational learning.

This study has several strengths and limitations. Strengths include objective measures of weight change and use of previously tested instruments for information processing and psychosocial variables. Limitations include the short

Table 3. Results of group-, age-, and sex-adjusted model regressing six-month weight loss on information processing variables at six months and six-month changes in self-efficacy.*

	Unadjusted bivariate correlations with weight loss	Unadjusted bivariate correlation p-value	Unstandardized estimate **b**	S.E.	P-value	Effect size (standardized estimate **ß**)
Information processing variables:						
Elaboration	−0.411	0.003	−0.343	0.136	0.011	−0.423
User control	0.023	0.876	0.034	0.211	0.873	0.024
Novelty	0.167	0.187	0.310	0.242	0.199	0.172
Cognitive Load	0.059	0.630	0.190	0.390	0.626	0.061
Self-efficacy (WEL questionnaire; latent change from baseline to six months)	−0.182	0.123	−0.033	0.030	0.268	−0.158
Covariates						
Group	−0.222	0.051	−2.686	1.325	0.043	−0.228
Sex	0.293	0.003	4.697	1.665	0.005	0.301
Age	−0.200	0.090	−0.102	0.060	0.089	−0.205

*Models adjusted for covariates of randomized treatment group, age, and sex; Negative coefficients correspond to lower weight at six month than at baseline (i.e. weight loss).

duration (6 months) and a small, mostly white, female, and educated population; significant missing data on all variables at six months; and potentially a lack of power to detect moderate effect size of self-efficacy or information processing variables. In addition, information processing variables were examined at the six-month timepoint, limiting the ability to determine the true direction of the relationship between these variables and weight loss. Examining how these variables might change over time would be important.

In conclusion, the findings of this study provide evidence for the need to target increases in elaboration in the design of mHealth interventions as a way to facilitate weight loss. The design of future mHealth interventions may want to target elements of an intervention that could potentially increase elaboration, such as making information personally relevant, ensuring the source of information seems credible, and providing effective modeling of healthy behaviors. Future research may wish to test if elaboration is also an important target for interventions using different technologies, such as texting, or targeting different health behaviors, such as smoking.

Clinical trials registry number: NCT02632461 (clinicaltrials.gov).

Declaration of conflicting interests: The author(s) declared the following potential conflicts of interest with respect to the research, authorship, and/or publication of this article: Authors Adam Hoover and Erich Muth have formed a company, Bite Technologies, to market and sell a bite counting device. Clemson University owns a US patent for intellectual property known as “The Weight Watch”, USA, Patent No. 8310368, filed January 2009, granted November 13, 2012. Bite Technologies has licensed the method from Clemson University. Adam Hoover and Eric Muth receive royalty payments from bite counting device sales. The remaining authors do not have any conflicts of interest to declare.

Funding: The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This study was funded by the National Cancer Institute of the National Institutes of Health under award number R21CA18792901A1 (PI: Turner-McGrievy). The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

Peer review: This manuscript was reviewed by reviewers who have chosen to remain anonymous.

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