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Personal goal setting eHealth component associated with improved weight loss at 6 months: A mixed methods secondary analysis

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Abstract

Objective: Goal setting is a behavior change technique associated with improved change in outcomes. Digital (eHealth, mHealth) behavior change interventions often prescribe all goals with no opportunity for participants to create and track their own; thus, little is known about the types of goals participants create for themselves and their impacts on behavioral outcomes. This analysis describes the goals created by participants using an optional personal goal-setting component and evaluates the association between participant goal creation and weight loss in an eHealth adult weight loss intervention.

Methods: This represents a mixed methods QUANT-qual design to understand the types of goals users create for themselves and their impacts on behavior change outcomes. Qualitative codes were applied for the topic, behavior/outcome focus, adherence to SMART criteria, and repetition with count summaries. Quantitative analyses applied regression modeling to determine if the number of goals set was associated with the 6-month weight change, controlling for covariates.

Results: Participants ($n = 363$) set an average of 23.4 goals ($SD = 22.7$) over 6 months. Those who reached at least 5% weight loss set significantly more goals than those who lost between 1% and 4.99% or who lost <1% or gained weight (p's < 0.0001). Setting more personal goals was associated with significant weight loss reduction at 6 months, controlling for covariates (p's < 0.05).

Conclusions: Greater use of a personal goal-setting feature was associated with improved weight loss outcomes among active users. This can be a low-investment addition to digital behavior change interventions to contribute to improved outcomes.

Keywords

Digital health, goal setting, eHealth, engagement, weight loss

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Introduction

Overweight and obesity are leading contributors to preventable mortality and morbidities worldwide, including diabetes, cardiovascular disease, and several types of cancers.[1,2] Digital behavior change interventions (DBCIs) are cost-effective, scalable, and proven capable of altering obesogenic behaviors to improve weight management and lower odds of morbidity development.[3–10] Among other components, goal setting is often employed in these

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interventions to encourage self-regulation and self-monitoring, where goals are representations of desired states that a participant commits themself to achieve. Michie et al.'s *Behavior Change Technique* (BCT) *Taxonomy* operationalizes goal setting as an activity directed toward behaviors or outcomes, where participants must either set or agree on a goal according to terms of the desired behavior or outcome with practitioners.[11,12] For example, one may set a behavioral goal of achieving 150 active minutes per week to motivate exercise and monitor their active minutes to determine when their goal is met. Likewise, one may set an outcome goal to lose a number of pounds by the end of the week and check their weight regularly to mark progress.[10,13,14,15] Research has shown that including goal setting in both digital and in-person behavior change interventions is associated with improved effect sizes; however, results have been mixed, as goal setting effectiveness is known to be moderated by a number of factors including behavioral or outcome goal orientation, frequency of goal setting and review, goal commitment, task complexity, and provision of feedback.[16–20] In general, best-practice literature encourages setting SMART goals (i.e. "specific, measurable, attainable, realistic, and time-oriented") to increase the likelihood of adherence and measurable success, as compared to vague or non-specific goals.[21,22]

Most DBCIs assign goals to participants, often tailored using baseline measurements and scaling upward in difficulty over time (i.e. beginning a program requiring 2000 steps per day, scaling up to 10,000 steps per day over six weeks).[23–26] While research has proven these types of goals to be effective, in many of these programs participants must follow the program-defined goals and are not able to adjust the goals or set new ones. As a result, there is little known about the effect of allowing participants to set their own goals in digital weight loss programs. A systematic review of 29 weight management DBCIs found that two studies permitted participant-set goals, but the specific procedures and content were not discussed in the study papers.[27–29] This leaves some gaps in understanding if and how participants' goals may differ from prescribed program goals, and if they contribute to the same behavior change outcomes.

Locke and Latham's Goal Setting Theory asserts that user-created goals are similarly effective at eliciting behavior change performance as practitioner-prescribed goals.[22,30] The theory also posits that moderately high difficulty goals are ideal to evoke performance, but if a goal becomes too difficult, participants may judge it to be unachievable and withdraw from future efforts to attain it, damaging their self-efficacy in the process.[22,30] To prevent this, the theory advocates for user autonomy to scale goals down to be more achievable or allow participants to shift their focus to other types of goals to preserve or boost their self-efficacy and feelings of accomplishment.[22,31,32] Thus if a psychological theory holds within a digital setting, these self-written goals could act as a potential autonomous supplement to study-specific goals, potentially increasing performance of desirable behaviors.

The primary aim of this secondary analysis is to describe the types of goals participants created for themselves while enrolled in a digital weight loss program. A secondary aim of this analysis is to determine if usage of this optional component was associated with improved weight loss outcomes in the first 6 months of the parent intervention, with the hypothesis that increased usage of this component is associated with improved weight loss outcomes, controlling for covariates.

Methods

Study design and participants

Data for this analysis comes from LoseNow Physician Assisted (LNPA), a 12-month, 3-arm cluster-randomized controlled trial to promote weight loss.[33] In the full sample, participants ($N = 550$) living with overweight or obesity were recruited from 13 primary care physician clusters and randomly assigned to one of three intervention conditions: enhanced usual care (EUC), a tailored internet weight loss program (IWL), or the internet weight loss program plus physician advice (IWL + PCP). LNPA was a clinically registered trial with identifier NCT01606813, approved by the Institutional Review Boards at the University of North Carolina at Chapel Hill (#12-1661) and Penn State College of Medicine (#39237). Written informed consent of all participants was collected prior to baseline assessments and randomization. The primary outcomes are reported in Tate et al. (2022); to summarize, both intervention groups showed significantly greater weight loss compared to EUC by 6 and 12 months, but no significant differences between intervention groups were found.[33] Because the EUC group did not receive the intervention website, this analysis focuses solely on participants randomized to the two IWL arms and pooled observations into one group ($n = 363$) to maximize statistical power.

The IWL program was based on behavior change techniques and principles from the Diabetes Prevention Program and informed by previously effective weight control interventions by Tate and colleagues.[4,34,35] Among other components, the IWL website included lessons and resources, a self-monitoring diary for recording dietary intake, weight, and physical activity, computer-tailored feedback based on reported progress, graphical and milestone feedback pages, and a user message board. For further details, see Tate et al. (2022).[33]

On the first login of each week, the website prompted users to complete a "weekly check-in" before redirecting to the home page. This "check-in" page contained questions on perceptions of diet, exercise, and weight loss progress along with blanks that participants could use to write and track up to three goals for the week. The page would also list goals set in the previous week alongside icons that participants could use to identify if they achieved that goal, as well as an option to "keep the same" and reinstate that goal for the current week. These unstructured goals were not measured or addressed in digital feedback. The only guidance participants received for this goal-setting component was a hyperlinked prompt leading to recommendations for setting specific, measurable, attainable, realistic, and time-oriented (SMART) goals to be more successful, which was present on every "weekly check-in" page.[21] This analysis represents a QUAN-*qual* mixed methods design informed by Morse and Niehaus to describe participant utilization of this optional goal setting component and analyze if goal creation is associated with 6-month weight change outcomes.[36] The outcome of 6 months, rather than 12 months, was selected as both engagement (i.e. usage and interaction with the digital program interface) and weight loss tend to be higher in the first 6 months of an intervention than in later months, and this study aimed to assess the impacts of active usage of the eHealth website.[37–43]

Measures

Weight change. Participant's body weight was clinically measured during physician office visits at baseline and 6 months. For descriptive purposes, participants were also subdivided into groups of those who lost ≥5% of starting body weight, those who lost 1–4.99%, and those who lost <1% or gained weight.

Total goals set. The total number of personal goals set by each participant was calculated by summing every goal entry across the 6-month subsample of the intervention containing any numerical or text characters into a single count variable.

Total logins. Participants were required to log in to the LNPA website each time they accessed it; however, the "check-in" page with goal setting entries only appeared on the first login of each week. Because of this, it was reasoned that any logins beyond one per week would indicate engagement with other website materials. Thus, total logins are included as a covariate in regression models to indicate engagement with other aspects of the IWL website.

Data analysis

Qualitative analysis. Descriptive analysis of written goals were coded by the first author (LH) using the framework method by Gale et al. to identify and describe the attributes of participant-created goals over 6 months, with descriptive counts included to provide insight for frequency and apparent preference of goals.[44,45] After a familiarization phase during data cleaning, (LH) engaged in open coding for recurring goal topics within the full dataset, inductively creating codes for goal type based on repetition, topical similarity, or novelty. The preliminary codebook was then reviewed with co-authors (BN, DT) to condense codes to essential "parent" and "child" sub-codes for topics of goals set. Any uncertainties in coding were addressed via unanimous consent among co-authors (LH, BN, DT), who have no disputes to report. The full analytic framework for this dataset including these code groupings can be found in Table 1. There was no double-coding in this framework. In the event that a goal could satisfy multiple type criteria, (i.e. "follow the (LNPA) dietary plan" could satisfy *diet* or *adherence & motivation* code groups) a unanimous decision was made to determine the root topic of the goal and assign its code (in this case, *adherence & motivation*).

Goals were deductively coded as behavior or outcome goals as characterized by the BCT taxonomy.[46] A third category, "orientation: unspecified," was applied in the rare instance that the team could not determine orientation of an entry based on BCT criteria. To promote inter-rater consistency and reliability, the decision was made to code goal entries as 1 if they sufficiently met all SMART criteria and 0 if they did not.[47] For example, "*Exercise 250 minutes or more for the week*" and "*Drink 64 plus oz of water a day"* were considered SMART goals, while "*Make better*

Table 1. Descriptive statistics.

Variable	Frequency (%)	Mean (SD)	Median (IQR)
Participant logins		99.03 (178.4)	33.0 (103.5)
Total goals set	9501 (100%)	29.0 (22.9)	15.0 (39.0)
Goals set per week		2.4 (1.1)	
Behavior goals	4325 (45.8%)		
Outcome goals	2776 (29.2%)		
Undetermined goals	534 (5.6%)		
Non-goal entries	1841 (19.4%)		
SMART goals	1379 (14.5%)		
Verbatim repeated	6445 (67.8%)		
Unique Entries	3506 (32.2%)		
Self-report "Achieved"	2923 (30.8%)		

SD: standard deviation; IQR: interquartile range.

choices," "*smaller portions,*" "*no excuses*" and "*eat less*" were not. Empty goal entries were not included in this count. Any disagreements were discussed by co-authors (LH, BN, DT) until 100% agreement was reached. An additional dummy coded variable for verbatim repeated goal entries was created, such that if two or more entries from the same participant contained identical text/numeric characters, suggesting the user applied the "keep the same" website function, copied and pasted the goals, or used a device's autofill function, they would be coded as 1. However, if two of the same goals were present but written differently, they would not be coded as verbatim repeating, or 0.

Quantitative analysis. As treatment between the two intervention groups were identical aside from the receipt of additional physician health advice, which did not contain content related to goal setting participants in these two groups were collapsed together to maximize statistical power. Following qualitative coding and analysis, descriptive statistics were applied to the dataset including frequencies, means, and paired t-tests for significant differences based on 6-month weight change groupings. Descriptive statistics of goal attributes based on qualitative coding were also conducted.

After confirming all variables satisfied assumptions of generalized linear modeling, two models were specified using age, sex, and race as sociodemographic control covariates. Age is mean-centered to promote interpretability. Weight change is operationalized as a residualized change score, entering baseline weight as a control covariate in regression equations to permit other covariates to predict the changeable variance in weight not explained by baseline levels. The first model regressed weight change onto total goals set. The second model regressed weight change onto total goals set with total logins as an additional covariate indicating overall website usage. All models used a residualized change score for weight change, entering baseline weight as a control covariate in regression equations to predict the changeable variance in weight not explained by baseline levels. Approximately 15% of this sample (n = 55) is missing 6-month weight measurements with no clear pattern to this missingness. To address this, we imputed missing weights using multiple imputation via chained equations to pool point and standard error estimates across $m = 20$ iterations to account for data assumed missing at random.[48,49] All analyses were organized and conducted using Microsoft Excel and R statistical software.[50]

The first author (LH) designed this mixed methods study and takes full responsibility for coding and analyzing of all data. At each phase of codebook development, coding, and analysis, co-authors (BN, DT) were consulted for input, supervision, and approval. All study authors have reviewed and vouch for the accuracy and completeness of the reported data.

Results

Participant characteristics

Participants randomized to the IWL website (n = 363) were mostly female (71.9%), white (86.9%), non-Hispanic (96.1%), identified as heterosexual (96.1%), with a mean age of 51.9 years (SD = 10.9; median = 53.1). Many participants were employed (69.2%), attended ≥4 years of college (43.9%) or had some (1–3 years) college education (36.4%), with annual income greater than $75,000 (39.13%). Participants had an average weight of 97.99 kg (SD = 18.7; median = 96.2) and an average BMI of 35.4 (SD = 5.5; median = 34.5) at baseline.

Types of goals set

During the first 6 months of the LNPA program, participants logged into the website an average of 99.03 times (SD = 178.4; median = 33.0). Of the users, 25 never logged into the site though they did not significantly differ from the main sample on any measured sociodemographic variables. Across the full sample (n = 363), the mean number of goals set by 6 months was 23.4 goals per user (SD = 22.7; median = 15.0), with a mean of 25.13 goals set (SD = 23.7; median = 18.0) by 6 months among users who logged into the website at least once (n = 338).

Goal entries primarily focused on health behaviors, with 4325 coded as behavior-oriented goals (45.8%), compared to 2776 outcome-oriented goals (29.2%). Goal type could not be determined for 534 entries (5.6%), and 1841 entries were either blank or not considered goals (19.4%).

Few goals adhered to SMART criteria. Only 1379 entries (14.5%) were determined to meet full SMART criteria (LH). Descriptive statistics for the full dataset are summarized in Table 1. Thirteen total "parent" and "child" codes were inductively created to describe the created goals, summarized in Table 2 alongside the frequency, cumulative percentage, and quoted examples of each goal code from the dataset.

Most of the goal entries in this sample were verbatim repeated ≥2 times by participants; suggesting usage of either the "keep the same" feature to reinstate the same goal on the weekly check-in screen, copy and pasting the same entry, or similar. Approximately 6445 goal entries (67.8%) were repeated at some point by their writers, meaning only 3506 entries (32.2%) were unique across all participants over 6 months. Self-reported adherence to created goals was low, with participants clicking to identify that they "achieved" only 2923 (30.8%) of their previous week's goals, and 6578 recorded entries (69.2%) left unchecked and registered as "not achieved" within program records.

Table 2. Goal topics.

Code	Frequency (%)	Example quote
1. Diet	2854 (30.0%)	"eat more fruits and veggies"
1a. Water	348 (3.7%)	"drink more water"
2. Exercise	2279 (24.0%)	"Exercise at least 30 minutes 4 days this week"
3. Weight loss	243 (2.6%)	"lose 2 pounds this week"
4. Adherence & motivation	736 (7.8%)	"follow plan"; "Log in every day"; "stay positive and motivated"
4a. Get back on track	178 (1.9%)	"Get back to the plan"; "After a vacation, getting back into program"
5. Behavioral skills	160 (1.7%)	"Prepare meals ahead of time"
5a. Time management	173 (1.8%)	"plan my weekend better"; "get up earlier to allow for morning workouts"
5b. Sleep	88 (0.9%)	"get more sleep"
6. Mental/ emotional health	140 (1.5%)	"take more time for myself"
6a. Negative emotional control	95 (1%)	"be less stressed"
6b. Reward	3 (0.03%)	"buy new exercise shoes"
99. Undetermined/ not a goal	364 (3.8%)	"limit holidays"; "xxxxxx"
0. No goal set	1840 (19.4%)	[Entry left blank]

In total, 9501 personal goal entries were coded, with full coding frequencies displayed in Table 2. Verbatim excerpts from website entries, including spelling/grammar errors, are identified via quotation marks and italic font. The majority of goals focused on eating behaviors and **Diet** (1) outcomes, including both promotion of healthy food and beverage groups ("*eat more fruits and veggies*") as well as restrictions or reminders such as ("*watch the beverages*"). After frequent recurrence, the **Water** subcode (1a) was added to distinguish goals specifically regarding water intake. This was the most common beverage intake variant, with only occasional mentions of other beverage types, such as restricting sodas. Goals regarding exercise and **Physical Activity** (2) were the second most prevalent "parent" code, and primarily focused on increasing structured physical activity or walking activities, rather than setting specific or measurable exercise goals. **Weight Loss** (3) was often set as a short-term outcome goal, such as losing a set number of pounds by the end of a given week. **Adherence & Motivation** (4) identifies goals focused on meeting LNPA program recommendations or to improve one's motivation to continue behavior changes to promote weight loss. A sub-type of adherence goal is distinguished by the in-vivo code "***Get Back on Track,***" encompassing goals to return to LNPA recommendations for diet, exercise, or weighing. Occurrences of this code are often phrased in an active tense and repeated for multiple weeks; indicating participants recognized a lapse in their own behavior or health outcomes and were independently striving to restore their previous status in the program. Some goals focused on development or performance of various **Behavioral Skills** (5), often focusing on dietary behaviors such as meal prepping or planning menus and meals ahead of time to manage calorie intake. Two subcodes were generated from the general behavioral skills "parent" code: **Time Management** (5a) was used when participants set goals organizing their daily schedules or making time for dedicated exercise ("*set aside time for exercise*"; "*find time to walk 3 times this week*"). Somewhat related to time management, the subcode **Sleep** (5b) was created due to the novelty of participants setting goals to budget increased time for nightly sleep or for scheduled rests during the day.

Not all goals were related to the program itself, but focused on holistic wellness during the program. The code **Mental/Emotional Health** (6) indicates goals either involved with a promotion of positive outlooks or resilience to remain positive following a lapse ("*be more positive*"; "*keep positive mindset after i've made poor eating choices conducive of healthy eating/living*"). Other examples include setting goals to promote mental/emotional self-care ("*take more time for myself*") or general self-forgiveness ("*don't be so hard on myself*"). The subcode **Negative Emotional Control** (6a) was deductively created due to its similarity to the BCT of the same name, involving a removal of some negative mental/emotional factor, often to reduce or eliminate stress ("*be less stressed*"), to improve resilience to unexpected stressors ("*learn how to better deal with things that come up unexpectedly*"), or even as diary reminders to adjust mental outlook ("*Stop thinking that this study is reminding me of what a failure I am at losing weight.*").[46] The rarest code, **Reward** (6b), only occurred 3 times ("*buy new exercise* *shoes*" and "*reward myself,*" which was repeated twice). Lastly, the code **Undetermined** (99) was used as a catch-all code for entries which were not goals – or not clearly identifiable as goals ("*I'd like to be responsible for my own health*"; "*Wonder why this is so hard*"; "*limit holidays*"), or random character strings ("*xxxxxx*"). We determined that saturation was reached by 6 program months across participants, as no new codes or themes were identified, and only counts of existing codes were increasing.[51–53]

Quantitative analyses

Of the 363 participants randomized to the IWL and IWL + PCP groups, n = 266 possess complete clinical weight change data for the following descriptive summary analyses: Mean weight loss across these individuals was −4.72 kg (SD = 5.8) at 6 months. Those who reached clinically significant weight loss of ≥5% baseline bodyweight (n = 107) set an average of 37.6 goals (SD = 26.7; median = 44.0) over 6 months, including repeated goals. This was significantly greater than those who lost between 1% and 4.99% of baseline weight (n = 89), who set an average of 29.21 goals (SD = 22.6; median = 23.0; $p < 0.0001$). Both of these groups set significantly more personal goals those who lost < 1% or gained weight (n = 70), who set an average of 17.5 goals (SD = 16.04; median = 12.0; p's < 0.0001).

The first pooled model regressing total personal goals set onto the residualized change score of 6-month weight is summarized in Table 3. The primary results of this model show that each one-unit increase in the number of total personal goals set over 6 months was significantly associated with 0.085 kg greater weight loss at 6 months, controlling for covariates (SE = 0.013; $p < 0.0001$).

The second model, adding total logins as an additional covariate to indicate overall program engagement regressing onto a residualized change score of 6-month weight is summarized in Table 4. While total website logins did explain some of the variance in 6-month weight change, the effect of total goals set remained significant. To interpret the results, each one-unit increase in the number of total personal goals set was significantly associated with 0.04 kg greater weight loss at 6 months, controlling for covariates (SE = 0.013; $p = 0.002$). In this same model, a one-unit increase in the total number of logins was significantly associated with 0.015 kg greater weight loss at 6 months, controlling for covariates (SE = 0.001; $p < 0.0001$). The addition of logins appeared to improve model fit, as the pooled R^2 increased from 0.923 in Model 1 to 0.942 in Model 2 with a bootstrapped pooled 95% confidence interval of (0.0123, 0.016).

Dummy-coded probing analyses for behavior or outcome orientation, SMART criteria adherence, and repetition were all nonsignificant in this sample and are not reported here. Among control covariates, age was significant across both models, such that a one-unit increase in age at baseline above the sample mean (51.9 years) was associated with an approximate 0.065 kg greater weight loss at 6 months in the full Model 2, controlling for covariates (SE = 0.026; $p = 0.011$).

Table 3. Pooled summary of Model 1: total goals set (N = 363).

Variable	Coefficient (SE)	95% CI	p-value
Intercept	5.356 (1.683)	(2.057, 8.655)	$p = 0.002$
Baseline weight	0.924 (0.017)	(0.891, 0.957)	$p < 0.0001$
Total goals set	−0.085 (0.013)	(−0.110, −0.059)	$p < 0.0001$
Age-mc	−0.102 (0.030)	(−0.161, −0.043)	$p = 0.001$
Sex	−0.190 (0.685)	(−1.533, 1.153)	$p = 0.782$
Race (Black)	1.083 (0.920)	(−0.720, 2.886)	$p = 0.241$
Race (Other POC)	2.306 (1.466)	(−0.567, 5.179)	$p = 0.119$

Notes: SE: standard error; CI: confidence interval; mc: mean-centered; POC: people of color.

Table 4. Pooled summary of Model 2: Goals + Logins (N = 363).

Variable	Coefficient (SE)	95% CI	p-value
Intercept	4.777 (1.542)	(1.755, 7.799)	$p = 0.002$
Baseline weight	0.936 (0.016)	(0.905, 0.967)	$p < 0.0001$
Total goals set	−0.040 (0.013)	(−0.065, −0.014)	$p = 0.002$
Total logins	−0.015 (0.001)	(−0.017, −0.013)	$p < 0.0001$
Age-mc	−0.065 (0.026)	(−0.116, −0.014)	$p = 0.011$
Sex	−0.667 (0.619)	(−1.880, 0.546)	$p = 0.283$
Race (Black)	0.333 (0.849)	(−1.331, 1.997)	$p = 0.695$
Race (other POC)	2.524 (1.353)	(−0.128, 5.176)	$p = 0.065$

SE: standard error; CI: confidence interval; mc: mean-centered; POC: people of color.

Discussion

This analysis describes the types of goals that participants in a digital weight loss intervention created for themselves and integrates evidence that increased usage of a personal goal creation and tracking component is associated with improved weight loss outcomes. These results support the study hypothesis that people who create more goals for themselves tend to lose more weight during a weight loss program than those who create fewer.[10,12,13,27] As this goal creation component was largely unstructured and self-directed, it is possible to glean insights into the types of goals participants choose to set as priorities for themselves during the parent study and the degree to which these goals align with program interests, since participants may have different interests than that of the structured program.[54]

While it was not surprising that the majority of goals set during a weight loss program focused on diet, physical activity, and weight, this finding may instill some confidence that when given the freedom to set any goals they want, participants motivated to use the program will likely create entries aligned with that program. Notably, many of the behavioral skill goals created by participants were learning goals within the diet and physical activity "parent" code groups, focused on acquiring knowledge and skills which could be used to meet other high difficulty goals.[22] The high number of learning skill goals related to meal prepping and menu planning might imply that these were created during struggles to adhere to program calorie goals for promote weight loss, and indicate a need for improved skill-building exercises for participant autonomy support in this type of intervention.[55,56] These findings echo recommendations from Swann et al.'s review highlighting a need to correctly specify learning goals for participants who may not be fully equipped to attain difficult performance goals in the context of physical activity goals, and warn of potential issues with program adherence related to prescribing difficult performance goals which might exceed a participant's capabilities too early.[57]

The creation of adherence and motivation goals might indicate the degree that a given participant may be struggling in the program and at risk of a lapse. Particularly the in-vivo "get back on track" code, which was often repeated for multiple weeks among several participants near the end of their recorded goal setting activity, indicates an acknowledgement of being in a lapse and a desire to return to a successful state in the program. This suggests both that creating these goals alone may not be sufficient to return to program recommendations and that these participants may have required more assistance than what was programmed into the DBCI. In the future, if an intervention were to include a personal goal creation component similar to the one analyzed here with a keyword monitoring system to identify these sorts of goal entries, it could signal the program to send additional resources to promote goal attainment and lapse prevention when participants would presumably be more receptive to that type of tailored content.

Results from this analysis can help to inform future message tailoring efforts in weight management DBCIs. For example, based on the recurrence of entries relating to water consumption, it might be beneficial to include not only messages recommending reductions in sugar-sweetened beverage consumption to help achieve calorie goals, but possibly messages and/or small goals related to increasing water consumption.[58,59] While the code related to improving sleep was unexpected, it could indicate an opportunity to incorporate messages addressing tiredness or exhaustion as commonly perceived barriers to increasing physical activity.[60] Entries focusing on mental/emotional health often involved maintaining optimistic outlooks, practicing self-forgiveness, as well as resilience to struggles during the program. These types of goals might also suggest an opportunity to consider holistic wellness during the design of lifestyle intervention messaging libraries to promote participant wellbeing and resiliency for goal setting and striving behaviors. Adaptive tailoring using these user-created goals could be utilized in future interventions to tailor intervention content to be more relevant to participant priorities, where applicable, and potentially increase the likelihood of goal commitment.[57]

Despite the variety of goal topics created using this component, many of the goals themselves were of low rigor. Most goals did not meet SMART criteria (85.5%) despite a linked resource on the same screen. Nonetheless, while these goals may have a low-rated *quality*, writing a greater *quantity* of goals was found to significantly contribute to improved weight loss outcomes, controlling for website logins.[61] Fleig et al. report similar results regarding a similar BCT, action planning, finding that less-specific action plans contributed to a greater desirable change in outcomes than more complex action plans.[46,62] Additionally, in their systematic review and meta-analysis of goal setting in digital physical activity promotion interventions, McEwan et al. found goal specificity was not associated with differences in effect sizes.[19] If this is an avenue of interest for future intervention research, it may be worthwhile to consider testing components such as interactive practice tutorials guiding SMART goal creation, as this analysis indicates that providing written instructions alone may be insufficient to promote this activity.

The opportunity to create and track personal goals in addition to prescribed program goals can provide a small step to increase participant autonomy in digital interventions. According to the Self-Determination Theory, supporting participant autonomy in ways such as this could help promote participants' perceived responsibilities for their own status in a program and potentially increase their investment in the program.[63–65] Future studies may wish to more specifically measure feelings of participant autonomy and control associated with goal setting within digital interventions, possibly using dedicated intervention designs to randomize access to this type of component.

This study has several limitations, including an inability to fully control for the effects of general program adherence (e.g. reducing calorie intake and increasing physical activity) or utilization of other website components, which may explain some variance in the observed relationship between total goals set and weight loss and could enable commentary on a potential intention–behavior gap.[66] This study is also unable to determine the direction or temporality of effects, only association, as it cannot determine if users who set more goals for themselves lost more weight or those who were successfully losing weight had greater confidence and self-efficacy to set more goals for themselves.

However, this study also has some strengths, including its novelty at being the first to describe and quantify the types of goals participants set in a long-term digital weight management intervention in a large dataset. Second, while the study sample may have lacked racial and ethnic diversity, it was more diverse than other types of eHealth interventions in other aspects: including that it was >25% male, included >50% of participants who did not have a Bachelor's degree or equivalent, and included older participants living with diabetes, hypertension, and other comorbidities. Thus, these findings may be particularly relevant for those aiming to conduct future behavioral interventions within a primary care setting.

Conclusions

Including a personal goal creation component as part of a DBCI can enable large amounts of information to be collected from participants, which could be used to inform more personalized content tailoring in future intervention designs, and its usage was associated with increased 6-month weight loss in this analysis. It will be helpful for future studies to include and evaluate this type of component to more clearly determine the extent that creating and achieving these personal goals have on behavioral performance, intervention engagement, and adherence.

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