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ORIGINAL ARTICLE

Clinical Trials and Investigations

Predicting high-risk periods for weight regain following initial weight loss

Kathryn M. Ross[1] | Lu You[2,3] | Peihua Qiu[2] | Meena N. Shankar[1] | Taylor N. Swanson[1] | Jaime Ruiz[4] | Lisa Anthony[4] | Michael G. Perri[1]

[1]Department of Clinical & Health Psychology, College of Public Health and Health Professions, University of Florida, Gainesville, Florida, USA

[2]Department of Biostatistics, College of Public Health and Health Professions & College of Medicine, University of Florida, Gainesville, Florida, USA

[3]Health Informatics Institute, University of South Florida, Tampa, Florida, USA

[4]Department of Computer and Information Science and Engineering, Herbert Wertheim College of Engineering, University of Florida, Gainesville, Florida, USA

Correspondence
Kathryn M. Ross, Department of Clinical & Health Psychology, University of Florida, Gainesville, FL 32610-0165, USA.
Email: kmross@phhp.ufl.edu

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Abstract

Objective: The aim of this study was to develop a predictive algorithm of "high-risk" periods for weight regain after weight loss.

Methods: Longitudinal mixed-effects models and random forest regression were used to select predictors and develop an algorithm to predict weight regain on a week-to-week basis, using weekly questionnaire and self-monitoring data (including daily e-scale data) collected over 40 weeks from 46 adults who lost ≥5% of baseline weight during an initial 12-week intervention (Study 1). The algorithm was evaluated in 22 adults who completed the same Study 1 intervention but lost <5% of baseline weight and in 30 adults recruited for a separate 30-week study (Study 2).

Results: The final algorithm retained the frequency of self-monitoring caloric intake and weight plus self-report ratings of hunger and the importance of weight-management goals compared with competing life demands. In the initial training data set, the algorithm predicted weight regain the following week with a sensitivity of 75.6% and a specificity of 45.8%; performance was similar (sensitivity: 81%–82%, specificity: 30%–33%) in testing data sets.

Conclusions: Weight regain can be predicted on a proximal, week-to-week level. Future work should investigate the clinical utility of adaptive interventions for weight-loss maintenance and develop more sophisticated predictive models of weight regain.

INTRODUCTION

Behavioral interventions produce clinically meaningful weight losses in adults with obesity [1], but long-term maintenance remains a challenge [2]. Although there are substantial physiological mechanisms contributing to weight regain [3–5], on a behavioral level, regain has been closely linked with decreased adherence to the weight-management behaviors used to produce initial weight loss [2, 6, 7]. As a result, current clinical guidelines conceptualize obesity within a chronic disease model, necessitating continual care and long-term treatment provision [1, 7–9].

Existing "extended-care" programs typically provide long-term support through monthly intervention sessions delivered either in-person or via telephone [10]. Importantly, these programs improve adherence to weight-management behaviors and reduce weight regain compared with no-contact or educational control conditions [10–12]. Although statistically significant, the impact of these programs on weight regain has been modest (~1.6 kg less regain vs. control at 12 months) [11], and there tends to be high individual variability in outcomes [2], suggesting a need for novel intervention approaches.

Newer, adaptive intervention models (e.g., just-in-time adaptive interventions) offer promise to improve long-term maintenance of health behaviors by monitoring individuals' emotional, physical, and/or environmental state and using context triggers to deliver intervention at critical, high-risk times [13]. For example, Alcohol-CHESS [14, 15] uses information from a daily questionnaire assessing negative affect, lifestyle balance, recent alcohol/drug use, and progress toward individual goals, combined with smartphone-based sensor information, to assess risk status in individuals following release from residential treatment for alcohol dependence. When individuals are deemed at high risk, the smartphone application delivers tailored intervention strategies to provide "just-in-time" support. Compared with usual treatment, Alcohol-CHESS reduces risky drinking days and improves likelihood of abstinence [15].

A key challenge to developing similar interventions for weight-loss maintenance is that little is known regarding how to proximally predict weight regain. Substantial foundational work was completed for the development of Alcohol-CHESS, including analyses of a rich longitudinal data set (including results from the weekly check-in discussed above, collected over 8 months) to develop predictive models of relapse [16]. Our research group collected a similarly rich data set during a 12-week internet-based weight-loss program followed by a 40-week observational maintenance period and used these data to explore week-to-week predictors of weight loss and regain [17]. Throughout the intervention and maintenance periods, participants were asked to log on to a study website at the end of each week to report self-monitoring data (weight, caloric intake, and physical activity) and complete an 11-item questionnaire designed to assess constructs hypothesized to be proximally associated with weight change [17]. Results confirmed the importance of self-monitoring for preventing weight regain after initial weight loss and identified a number of self-report questionnaire items that proximally predicted weight regain during the maintenance period. Although informative, this previous study did not identify potential thresholds for these variables, which are necessary to develop interpretable decision rules to alert clinicians or trigger real-time intervention provision. In the current study, we aimed to build on this prior work and develop a predictive algorithm of "high-risk" periods for weight regain after initial weight loss, identifying the key combination of variables (and specific thresholds for these variables) to predict weight regain on week-to-week basis. As we proposed to study *regain*, initial models were developed using data only from participants in this previous study (Study 1) who experienced clinically meaningful weight losses (i.e., ≥5% of initial weight [18]) during the initial intervention. To ensure that the algorithm was not overfitted to this data set, performance was evaluated in two additional samples: 1) remaining Study 1 participants excluded from initial model development (i.e., due to weight change <5%), and 2) adults who reported recent weight loss recruited for a separate pilot study (Study 2) evaluating a smartphone mHealth app; these participants were asked to self-monitor weight, dietary intake, and physical activity daily and complete questionnaire items at the end of each week over a 30-week observational period.

Study Importance

What is already known?

- Behavioral interventions are effective at producing clinically meaningful weight changes, but long-term maintenance remains a challenge.
- Little is known regarding what factors can proximally predict weight regain after the end of an initial weight-loss program, precluding the development of adaptive interventions for weight-loss maintenance.

What does this study add?

- We developed and tested an algorithm that uses self-monitoring data and two brief self-report items, collected at the end of a week, to predict (with sensitivity of 76%–82% and specificity of 30%–46%) whether an individual is at risk of weight regain the following week.
- Key variables retained in the final algorithm included frequency of self-monitoring of weight and caloric intake along with participant ratings of hunger and the importance of staying on track compared to competing life demands.

How might these results change the direction of research or the focus of clinical practice?

- Results demonstrate that it is possible to proximally predict weight regain on a clinically relevant week-to-week basis, supporting development and refinement of future predictive algorithms that can identify high-risk periods for weight regain.
- This algorithm will allow researchers to investigate the clinical utility of adaptive interventions that provide additional intervention at times when individuals are at high risk for weight regain.

METHODS

Using data from two previous studies, we aimed to develop and evaluate an algorithm for predicting, on a week-to-week level, high-risk periods for weight regain after initial weight loss. Study 1 included adults with overweight or obesity (age = 18–70 years, body mass index [BMI] ≥25 kg/m^2) who completed a 12-week internet-based weight-loss program followed by a 40-week observational "maintenance" period, during which no intervention was provided. Study 2 included a sample of 30 adults (age = 18–70 years, BMI = 18–45 kg/m^2) who reported recent weight loss (≥5% during the 2 years prior to enrollment) and were enrolled in a pilot study evaluating usability and acceptability of a smartphone mHealth app for self-monitoring dietary intake, physical activity, and weight in the context of weight-loss maintenance.

Study 1: Participants

Study 1 was a worksite-based weight-loss program provided to 75 employees and dependents of employees of a large health care corporation in Providence, Rhode Island. Full details regarding recruitment and intervention outcomes have been published [19]. To be included in current analyses, participants from the parent study must have self-weighed using the study e-scale and reported weekly questionnaire data for at least 1 week during the maintenance period. Approval for the parent study was obtained from The Miriam Hospital Institutional Review Board (IRB) and approval for the current analyses was obtained from the University of Florida (UF) IRB.

Study 1: Intervention

Participants were provided with a 12-week internet-based weight-loss program [19] based on the Diabetes Prevention Program [20]. Participants attended one in-person group visit, at which they received basic weight-loss education, were given initial goals for caloric intake (1200–1800 kcal/day, based on initial weight) and physical activity (gradually increasing moderate- to vigorous-intensity activity to reach an eventual goal of 200 min/week), and were taught how to use the study website and study-provided tools (a calorie reference book, a pedometer, e-scale, and paper records) to self-monitor dietary intake, physical activity, and weight. Participants were provided with weekly interactive video lessons and asked to log into the study website by midnight on Sunday each week to self-report self-monitoring data (caloric intake, minutes of physical activity, and weight for each day over the past week) and to answer a brief (11-item) questionnaire querying constructs hypothesized to be proximally associated with weight change (although participants were asked to complete the questionnaire each Sunday evening, it was available from 12:00 a.m. Monday until 11:59 p.m. Sunday) [17]. Each Monday morning, participants received automated feedback based on their self-monitoring data.

Following the end of the 12-week intervention, no additional intervention was provided, and participants no longer had access to intervention materials via the study website. Throughout the 40-week observational maintenance period, participants were asked to continue to login to the study website each Sunday to self-report a summary of their self-monitoring habits (number of days of self-monitoring caloric intake and weight, and total number of minutes of physical activity) and to complete the questionnaire; however, no feedback was provided. To support retention and data collection, small financial incentives ($1–10/week, maximum of $156 total) were provided for submitting data via the website (participants still received incentives for reporting 0 days of self-monitoring).

Study 1: Measures

Weight was assessed throughout the study using study-provided e-scales (BodyTrace, Inc.), which sent weights directly to research servers via the cellular network and which have been demonstrated to have good concordance with in-person weight assessment [21, 22]. Participants were asked to self-weigh first thing each morning, after using the restroom but before having anything to eat or drink [23]. The weekly questionnaire included 11 Likert-style items asking participants to rate (from 1 to 7) their positive mood, negative mood, stress, hunger, boredom with weight control efforts, temptation to eat foods not on their plan, temptation to skip planned physical activity, the degree to which eating choices were consistent with weight-loss goals, the degree to which physical activity choices were consistent with weight-loss goals, the amount of effort that it took to stay on track, and the importance of staying on track, compared with other demands in life (rationale for inclusion of these items, along with a copy of the full questionnaire, has been published previously [17]). Completed at the end of each week, this questionnaire asked participants to rate items over the prior week, with higher ratings indicating greater endorsement.

Study 2: Participants

Participants in Study 2 were adults who reported recent weight loss (≥5% during the 2 years prior to enrollment) recruited for a pilot study evaluating the usability and acceptability of a smartphone application being developed to support long-term weight-loss maintenance. This smartphone application integrated self-monitoring features and data capture to ultimately support the use of our final algorithm in an intervention context. Potential participants were recruited using flyers, newspaper/newsletter ads, and the UF Weight Management Registry, which included contact information for past weight-loss study participants who provided consent to be contacted for future studies. Using similar methods to the National Weight Control Registry [24], potential participants were asked to provide signed documentation of the amount and timing of their weight loss. Potential participants were excluded if they had history of bariatric surgery, were currently using weight-loss medications, had any physical limitations that prevented walking 1/4 mile without stopping, used a pacemaker, were currently pregnant, breastfeeding, planning to become pregnant, or were less than 2 years postpartum. Finally, Study 2 participants were included in current analyses only if they self-weighed using the study e-scale and reported questionnaire data for at least 1 week during the 30-week observational period. Approval for Study 2 was obtained from the UF IRB.

Study 2: Procedures

At the first study visit, participant height and weight were measured by study staff, and self-report questionnaires were completed via REDCap [25]. Participants were then provided with a BodyTrace e-scale and asked to install the study smartphone application

(MyTrack+). MyTrack+ synced data directly from the e-scale, used the FatSecret API [26] to allow individuals to self-monitor dietary intake and physical activity, and permitted researchers to push scheduled or random questionnaires directly to users. Participants were taught how to use these tools and asked to self-monitor weight, dietary intake, and physical activity daily. No additional intervention was provided.

A second study visit occurred 2 weeks after the first visit, at which participants were asked to provide feedback regarding the acceptability and usability of the MyTrack+ app. Participants were then asked to continue to use the scale and app to self-monitor weight, dietary intake, physical activity, and to complete study questionnaires pushed by researchers weekly over 30 weeks. Participants were compensated $30 for this second study visit and a final visit at the end of the 30-week period; however, no financial incentives were provided for completing questionnaires or self-monitoring using MyTrack+.

Study 2: Measures

Weight data were collected from the BodyTrace e-scales. Dietary intake and physical activity were collected from MyTrack+. The self-report questions that were retained following completion of analyses for Study 1 were pushed as a survey to participants at the end of each week (every Sunday evening) via MyTrack+; these data were downloaded from study servers to evaluate the performance of the algorithm developed from Study 1.

Statistical analyses

Analyses were conducted with R versions 3.4.1 to 4.2.2 and SAS version 9.4 (SAS Institute Inc.). Weight data were cleaned using methods described previously [27]. To determine if individuals were gaining or losing weight during a given week (defined as Monday through Sunday), local polynomial kernel smoothing procedures (using R package *locfit*) were applied to the observed weight data (calculating estimated weight as the weighted average of observed weights in the 2 weeks prior to and 2 weeks following a given timepoint; for gaps of >3 weeks between observations, a line was used to connect fitted curves at the start/end of the gap), and fitted values were used to estimate weight change each week (negative values represented weight loss and positive values represented weight gain).

First, a linear mixed-effects model with a backward elimination model selection procedure ($\alpha = 0.20$) was used to retain predictors (starting with the 11 self-report ratings along with three self-monitoring variables: frequency of self-monitoring caloric intake and weight and minutes of physical activity) that were most highly associated with weight change during the following week in the training data set. Second, random forest regression (R package *rpart*), a supervised machine-learning procedure, was used to fit tree models [28, 29] and determine which combination of predictors (and at which thresholds) best predicted magnitude of weight change, as a continuous variable, during the following week. Initially, a deep tree using all available predictors was fit; however, to avoid model overfit, this model was automatically trimmed (removing some predictors) using a complexity parameter developed via 10-fold cross-validation [28]. Next, given that a clinically meaningful threshold for assessing weight regain on a weekly level has not been established, to support clinical application of our model we evaluated a range of potential thresholds (ranging from 0.0 to 0.10 kg/week) for categorizing weekly weight regain. Given research evidence and theoretical support for the importance of intervening as early as possible in a lapse cycle [30–32], we selected the threshold that maximized model sensitivity (i.e., ability to correctly identify individuals who gained weight the following week); no minimum threshold for specificity (i.e., the ability to avoid false positive signals) was used. The final model was evaluated first using data from remaining Study 1 participants excluded from model development and then using data from Study 2.

RESULTS

Description of study samples

Of the 75 participants in Study 1, seven were excluded for missing data. The 68 remaining participants lost an average (mean ± standard

TABLE 1 Participant demographics and baseline characteristics, by sample

Characteristic	Study 1		Study 2
	Training data set, $n = 46$	Testing data set, $n = 22$	Testing data set, $n = 30$
Age, mean (SD), years	52.2 (9.4)	48.0 (11.7)	38.9 (14.8)
Weight, mean (SD), kg	88.6 (19.3)	81.9 (9.5)	82.65 (20.4)
BMI, mean (SD), kg/m^2	31.3 (5.1)	30.6 (3.4)	28.1 (5.3)
Gender			
Female, *n* (%)	28 (61%)	19 (86%)	20 (67%)
Male, *n* (%)	18 (39%)	3 (13%)	10 (33%)
Race[a]			
American Indian or Alaskan Native, *n* (%)	1 (2%)	0 (0%)	0 (0%)
Asian, *n* (%)	1 (2%)	0 (0%)	4 (13%)
Black or African American, *n* (%)	2 (4%)	5 (23%)	3 (10%)
White, *n* (%)	41 (91%)	15 (73%)	22 (73%)
Other, *n* (%)	1 (2%)	3 (14%)	1 (3%)
Ethnicity			
Hispanic or Latino, *n* (%)	1 (2%)	1 (5%)	5 (17%)
Not Hispanic or Latino, *n* (%)	45 (98%)	21 (95%)	25 (83%)

[a]Participants could select more than one race; thus, totals may exceed 100%.

deviation [SD]) of −6.19 ± 4.87 kg (6.84% ± 4.72% of initial weight) during the initial intervention and regained an average of 2.39 ± 3.75 kg (a 2.97% ± 4.64% increase) during the maintenance period; 46 participants lost ≥5% of their baseline weight during the intervention and were included in the initial algorithm development data set (i.e., the training data set), and 22 lost <5% and were included in the initial testing data set. In Study 2, 33 participants attended the initial visit; of these, three were excluded for missing data, leaving a sample of 30 participants for final algorithm testing. Across all three samples, participants were an average (mean ± SD) of 47.2 ± 13.0 years old and had a baseline BMI of 30.2 ± 5.0 kg/m^2; moreover, 68.4% identified as female and 76.5% as non-Hispanic White (Table 1).

TABLE 2 Final linear mixed-effects model predicting weight change the following week, selected via backwards elimination (with $\alpha = 0.20$)

Variable	Estimate	SE	*t*	*p*
Intercept	0.247	0.067	3.67	<0.001
Frequency of self-monitoring caloric intake, days	−0.014	0.004	−3.61	<0.001
Frequency of self-weighing, days	−0.019	0.006	−3.36	0.001
Eating choices consistent with weight-loss goals	−0.025	0.007	−3.42	0.001
Effort of "staying on track"	0.024	0.007	3.47	0.001
Hunger	0.012	0.007	1.69	0.091
Temptation to eat foods "not on plan"	−0.022	0.008	−2.79	0.005

Study 1 training data set participants ($n = 46$) submitted 1340 weekly questionnaires (mean ± SD: 29.1 ± 9.5 per participant; 72.8% ± 23.6% of possible weeks) and had a total of 9765 valid days of e-scale weights (212.3 ± 50.6 days/participant; 75.8% ± 18.1% of possible days). Study 1 testing data set participants ($n = 22$) submitted 679 weekly questionnaires (30.9 ± 11.5 per participant; 77.2% ± 28.7% of possible weeks) and had a total of 3457 valid days of e-scale weights (157.1 ± 73.3 days/participant; 56.1 ± 26.2% of possible days). Finally, Study 2 testing data set participants ($n = 30$)

TABLE 3 Sensitivity and specificity of the algorithm described in Figure 1 for detecting weight regain at various thresholds, using the Study 1 training data set

Potential threshold for determining weight regain (kg)	Sensitivity		Specificity	
	Estimate	SE	Estimate	SE
Weight change of 0.00	0.756	0.001	0.458	0.001
Weight change of ≥0.01	0.756	0.001	0.458	0.001
Weight change of ≥0.02	0.683	0.001	0.557	0.001
Weight change of ≥0.03	0.683	0.001	0.557	0.001
Weight change of ≥0.04	0.581	0.001	0.657	0.001
Weight change of ≥0.05	0.581	0.001	0.657	0.001
Weight change of ≥0.06	0.432	0.001	0.771	0.001
Weight change of ≥0.07	0.432	0.001	0.771	0.001
Weight change of ≥0.08	0.432	0.001	0.771	0.001
Weight change of ≥0.09	0.432	0.001	0.771	0.001
Weight change of ≥0.10	0.279	0.001	0.857	0.001

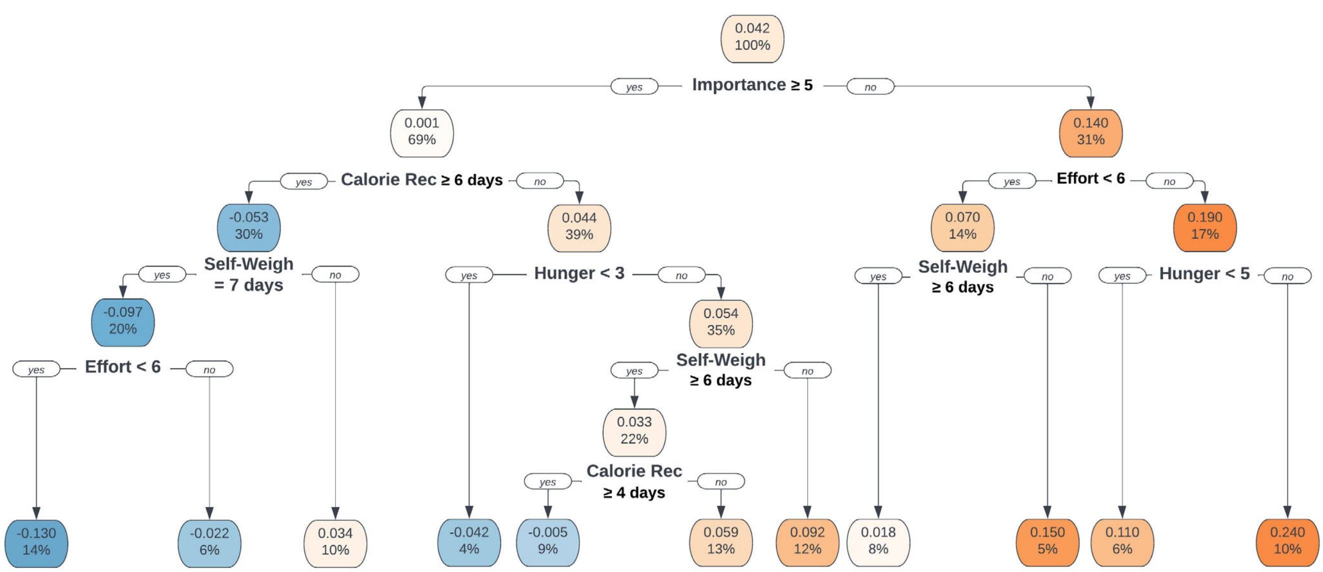

FIGURE 1 Initial regression tree model, predicting weight change (kg) the following week. Each node presents the proportion of participant weeks that fall into each node, along with the magnitude of weight change experienced the following week by those participants. Darker shades of blue represent greater weight loss (negative values) and darker shades of orange represent greater weight gain (positive values). Calorie Rec = Calorie records (i.e., days of self-monitoring caloric intake). [Color figure can be viewed at wileyonlinelibrary.com]

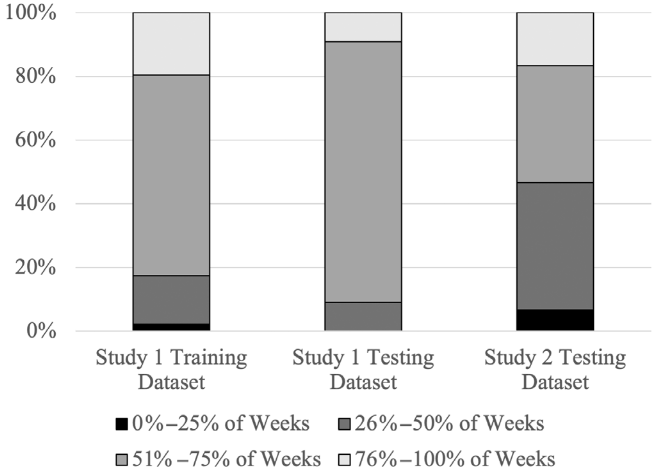

FIGURE 2 Proportion of participants within each sample experiencing weight regain on 0%–25% of weeks, 26%–50% of weeks, 51%–75% of weeks, and 76%–100% of weeks.

submitted 566 weekly questionnaires (18.9 ± 8.0 per participant; 62.9% ± 26.6% of possible weeks) and had a total of 3662 valid days of e-scale weights (122.1 ± 49.1 days/participant; 58.1% ± 23.4% of possible days). See online Supporting Information for additional details regarding missing data. The average weekly weight change was (mean ± standard error [SE]) 0.06 ± 0.29 kg in the Study 1 training data set, 0.08 ± 0.30 kg in the Study 1 testing data set, and 0.06 ± 0.49 kg in the Study 2 testing data set.

Algorithm development

Results of the backwards elimination model are displayed in Table 2; two self-monitoring variables and four of the self-report ratings were retained. These predictors were used in the random forest regression, with the addition of the self-report rating for the importance of staying on track compared with other life demands (as this variable had

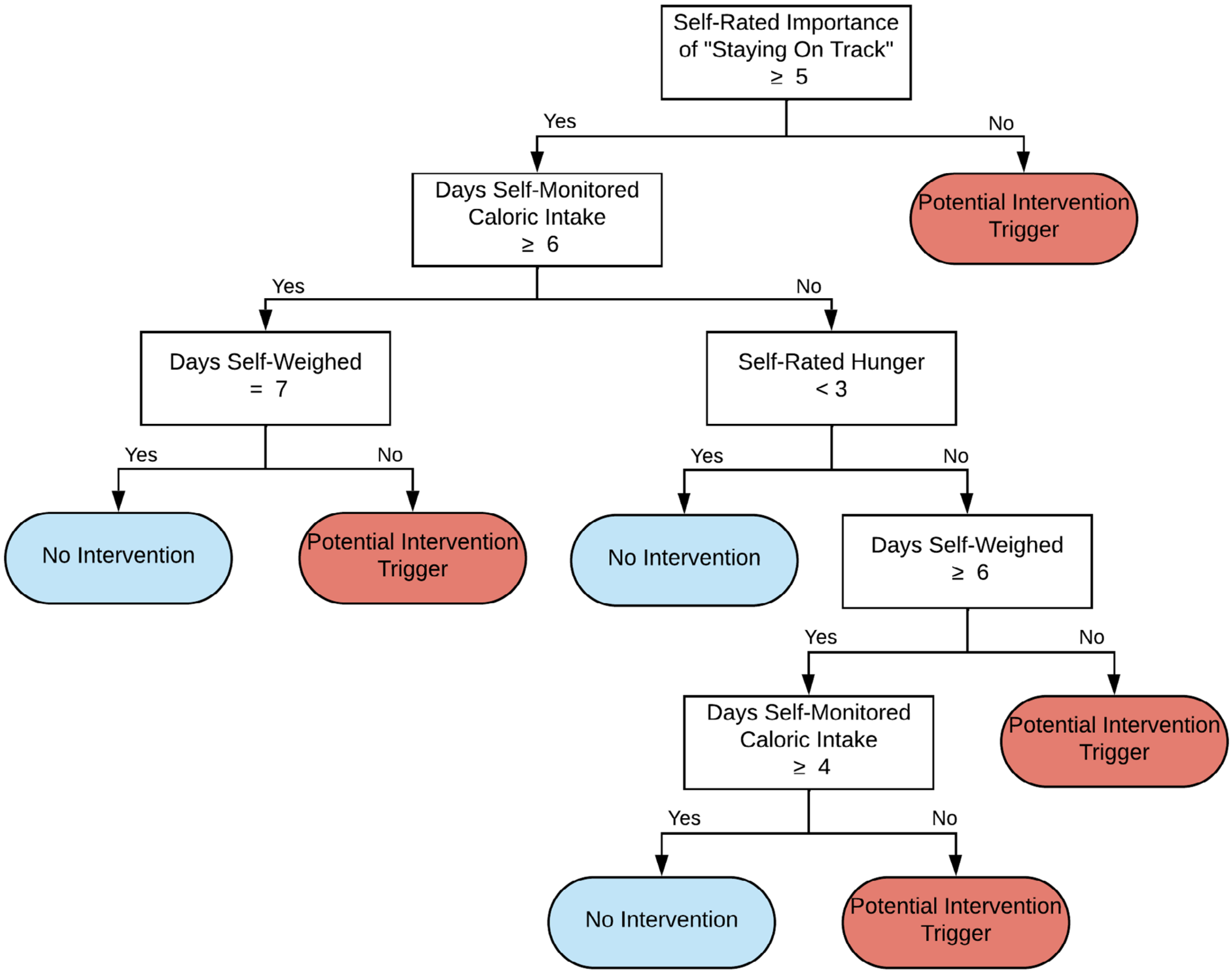

FIGURE 3 An example of the how the final decision-tree algorithm for predicting weight regain ≥0.01 kg the following week could be implemented to trigger intervention support. [Color figure can be viewed at wileyonlinelibrary.com]

only been removed in the final step of the backwards elimination procedure and our previous work [17], using univariate models, demonstrated that this variable was the second strongest of all rating items for predicting weight regain).

Figure 1 provides the initial regression tree model, with each node including the magnitude of weight regain experienced the following week and the proportion of person-weeks represented. Two self-monitoring variables (weight and caloric intake) and three of the self-report ratings ("importance of staying on track," the "effort it took to stay on track," and "hunger") were retained. Table 3 provides the sensitivity and specificity of this model for determining weight regain the following week with different cutoffs; for example, if 0.01 kg was selected as the threshold (i.e., weight change ≥0.01 categorized as "weight regain"), the model correctly identified regain 75.6% of person-weeks and correctly identified "not regain" 45.8% of person-weeks. The cutoff of 0.01 kg optimized model sensitivity and was thus selected; next, unnecessary branches were removed from the model in Figure 1 (see Supplement S2, Online Supporting Material). For example, if an individual's rating of the importance of staying on track was <5, weight regain ≥0.01 kg was the outcome regardless of ratings of effort or hunger or the number of days weight was self-monitored; thus, this branch was trimmed. Figure 2 presents patterns of weight regain observed using the selected threshold.

Figure 3 provides the final trimmed algorithm, exemplifying application for triggering intervention. Final sensitivity of this model for predicting weight regain the following week in the initial training data set was 75.6%, with a specificity of 45.8%. Sensitivity and specificity were 82.0% and 30.4%, respectively, in the Study 1 testing data set and 81.5% and 33.2%, respectively, in Study 2. If used to trigger intervention, this algorithm would do so on 47.9% of weeks in the Study 1 training data set, 63.2% of weeks in the Study 1 testing data set, and 48.1% of weeks in Study 2 (see details regarding "false" triggers and alternate thresholds in online Supporting Information).

DISCUSSION

The current study developed a predictive algorithm of high-risk periods for weight regain after initial weight loss by identifying the combination of variables (and thresholds for these variables) that predicted weight regain on a week-to-week level. Initial model results demonstrated that, for predicting proximal (next week) regain, key variables included the frequency of self-monitoring of weight and caloric intake along with ratings of whether eating choices were consistent with weight-loss goals, the effort of staying on track, hunger, and temptation to eat foods not on one's plan. Not all variables were retained via random forest regression, potentially due to existing associations among variables (e.g., it is likely that people who self-monitor dietary intake more frequently during a week are more likely to meet calorie goals that week, potentially minimizing the contribution of self-report ratings of consistency between eating choices and goals). Our final algorithm demonstrated that weight regain was best predicted by ratings of the importance of staying on track compared to competing life demands and hunger along with specific patterns of suboptimal adherence to self-monitoring caloric intake and weight. This algorithm performed similarly in two testing data sets (with sensitivity above 80% in both data sets) as it did in the initial training data set.

A trade-off of optimizing our algorithm for sensitivity was suboptimal specificity (i.e., our final algorithm would be unlikely to miss individuals at risk for weight regain, but there may be an excessive number of false triggers for intervention when it is not needed). Indeed, results demonstrated a high number of triggers in each sample (48%–63% of weeks); however, this rate also matched the high proportion of weeks of regain observed in Figure 2. We have justified this trade-off given research demonstrating the importance of responding quickly to weight regain for successful long-term weight-loss maintenance [30–32]; however, future work should aim to identify whether there is an optimal balance between model sensitivity and specificity in relation to cost-effectiveness and participant burden.

This study has several important limitations. First, maximizing algorithm sensitivity involved a trade-off of lower specificity, limiting the potential usefulness of the algorithm due to overidentification of "high-risk" periods; however, researchers can use results in Figure 1 and Table 3 to develop alternate versions of this algorithm for further testing and clinical applications. Second, algorithm development was limited to data collected during Study 1; it is possible that there are other important predictors of weight regain that were not captured. It is also possible that other variables not modeled in our current study (e.g., prior weight change; see Supplement S5, Online Supporting Material) may be important predictors of weight regain; thus, it is critical for future research to investigate other potential predictors that may improve model accuracy. Third, self-report data from Study 1 and questionnaire ratings from Study 1 and Study 2 were collected at the end of each week, leaving potential for recall bias. Moreover, these constructs likely vary on different orders of magnitude, thus data may be lost or captured inaccurately when rated over the course of a week (e.g., an individual is unlikely to provide the same rating of hunger over the course of a day, much less over a week). Finally, the sample was predominately middle-aged, non-Hispanic, and White, and average BMIs were lower than those typically observed in behavioral interventions (partly due to design, as Study 1 recruited individuals both with overweight and obesity and Study 2 recruited individuals who had recently lost weight), limiting generalizability to the broader population of adults with obesity. Future research should investigate whether the proximal predictors of weight regain differ in more representative samples.

Strengths of the current study include the use of rich longitudinal data sets for algorithm development and testing, including weekly self-report questionnaire and daily e-scale weight data collected over 40 weeks (Study 1) and 30 weeks (Study 2), and the replication of results in two separate samples with differing amounts of missing data and different methods for assessing frequency of self-monitoring. Although Study 1 was limited due to use of self-report for determining frequency of self-monitoring, Study 2 collected data directly from a smartphone application, limiting measurement error and bias related to self-report. The consistency of results observed across samples (and, in Study 1, across both participants who lost ≥5% of their initial weight and those who did not) supports the robustness of the final algorithm and suggests potential clinical utility for predicting weight gain more broadly (e.g., not just in individuals who have experienced ≥5% weight losses). The final model also has strong face validity, given current clinical knowledge and known associations between self-monitoring and successful weight-loss maintenance [24, 33, 34].

We see two critical next steps for this work. First, it is important to assess whether intervening at high-risk times can successfully prevent weight regain and thus promote long-term weight-loss maintenance. Our group is currently conducting a randomized clinical trial (NCT04116853) assessing the impact of providing extended-care intervention when individuals are at high risk for weight regain, using the algorithm developed in the current study. Given the high frequency of intervention triggered through the proposed algorithm, a related consideration is how this level of extended-care intervention support could be provided in the most cost-effective manner (e.g., potentially using lower-intensity intervention methods or newer technologies to supplement human contact).

Second, future work should focus on developing more refined algorithms for predicting weight change. Our group is currently collecting data using a similar weekly questionnaire, delivered on a random day each week (instead of at the end of each week), asking participants to rate items only as they pertain to that day (reducing the impact of recall bias), and querying additional constructs that may be associated with weight change (e.g., sleep habits). Future research should also examine whether patterns of predictors of weight regain may differ among groups or individuals and thus, whether algorithms should be modified at the group (e.g., based on individual age, race/ethnicity, or education level) or individual level (e.g., as is being done by Forman and colleagues [35–37] to predict dietary lapses during initial weight loss). Finally, future models may be improved by investigating the roles of weight variability, time, or patterns of missing data, or by the use of more sophisticated techniques (e.g., using cost-sensitive classifiers, which can more effectively balance risk of false positives vs. false negatives, or novel approaches such as dynamic statistical process control models [38]).

CONCLUSION

Overall, results of the current study demonstrate that weight change after the end of an initial weight-loss program can be predicted on a proximal, week-to-week level, providing a clinically relevant time period during which additional intervention could be offered to individuals at high risk for weight regain. Future work should aim to develop more sophisticated predictive models and to investigate the clinical utility of adaptive interventions for weight-loss maintenance.O

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CONFLICT OF INTEREST STATEMENT

The authors declared no conflict of interest.

ORCID

Kathryn M. Ross https://orcid.org/0000-0002-3628-766X
Lu You https://orcid.org/0000-0002-9400-2060
Peihua Qiu https://orcid.org/0000-0003-4439-9466
Meena N. Shankar https://orcid.org/0009-0005-3792-966X
Taylor N. Swanson https://orcid.org/0000-0001-7161-4980
Jaime Ruiz https://orcid.org/0000-0002-9139-6172
Lisa Anthony https://orcid.org/0000-0002-9617-2952
Michael G. Perri https://orcid.org/0000-0003-3651-1542

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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