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# Using Artificial Intelligence to Optimize Delivery of Weight Loss Treatment: Protocol for an Efficacy and Cost-Effectiveness Trial

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## Abstract

Gold standard behavioral weight loss (BWL) is limited by the availability of expert clinicians and high cost of delivery. The artificial intelligence (AI) technique of reinforcement learning (RL) is an optimization solution that tracks outcomes associated with specific actions and, over time, learns which actions yield a desired outcome. RL is increasingly utilized to optimize medical treatments (e.g., chemotherapy dosages), and has very recently started to be utilized by behavioral treatments. For example, we previously demonstrated that RL successfully optimized BWL by dynamically choosing between treatments of varying cost/intensity each week for each participant based on automatic monitoring of digital data (e.g., weight change). In that preliminary work, participants randomized to the AI condition required one-third the amount of coaching contact as those randomized to the gold standard condition but had nearly identical weight losses. The current protocol extends our pilot work and will be the first full-scale randomized controlled trial of a RL system for weight control. The primary aim is to evaluate the hypothesis that a

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Declaration of interests
The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Evan M. Forman receives royalties from Oxford Press for a published acceptance-based behavioral weight loss treatment manual and workbook and is on the Scientific Advisory board for Nutrisystem Health.

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RL-based 12-month BWL program will produce non-inferior weight losses to standard BWL treatment, but at lower costs. Secondary aims include testing mechanistic targets (calorie intake, physical activity) and predictors (depression, binge eating). As such, adults with overweight/obesity ($N$=336) will be randomized to either a gold standard condition (12 months of weekly BWL groups) or AI-optimized weekly interventions that represent a combination of expert-led group, expert-led call, paraprofessional-led call, and automated message). Participants will be assessed at 0, 1, 6 and 12 months.

### Keywords

mHealth; weight loss; diet; eating; artificial intelligence; machine learning

## Introduction

More than 70% of Americans have overweight or obesity[1,2], representing an unprecedented public health challenge. The gold standard treatment for obesity is behavioral weight loss (BWL), which can yield clinically significant outcomes (e.g., 7-10% weight loss, on average) when delivered by highly-trained weight loss coaches who provide frequent and sustained contact.[3-7] However, the scalability of gold standard treatment is limited by the availability of expert clinicians[8,9] and the high cost of treatment delivery (~$2,000/year'[10-13]), which greatly hinders the dissemination of BWL treatment at the population level.

## Tailoring by Treatment Intensity

Although one option to improve scalability of BWL is to lower treatment cost (e.g., by automating some intervention components or by lowering interventionist skill level), trials on such approaches have generally yielded disappointing weight loss outcomes (1-3%)[14-18]. An alternative approach to lowering treatment cost without compromising efficacy is to deliver lower-cost treatments to those individuals who respond adequately to these approaches (30-50% of individuals in lower-cost treatments reach 10% weight loss)[19-21] and reserve high-intensity treatments for individuals who are unable to benefit from low-intensity treatments. This tailored approach to treatment selection may prevent resources from being needlessly expended on individuals who can lose weight successfully with low-intensity treatment, as well as on individuals who have suboptimal responses, whether they are treated with full-intensity or lower-intensity BWL.

## Reinforcement Learning

An ideal method for efficiently allocating resources in this way is the artificial intelligence (AI) technique of reinforcement learning (RL), which learns the best actions to take (from a set of possible actions) by repeating these actions many times and tracking their consequences.[22,23] In the context of weight control, RL could monitor participants' weight losses in response to different interventions and optimize the assignment of interventions based on which yields the best outcomes for each individual and/or group of individuals (Figure 1). See Table 1 for example scenarios showing how AI can optimize BWL treatment.

## Preliminary Study

In a preliminary trial conducted by our group, 52 adults with overweight or obesity received 4 weeks of group treatment and then were randomized to receive 12 weeks of either gold standard weekly group treatment or 12 weeks of AI-optimized treatment using one of two algorithms (*individually optimized*, in which participants always receive their preferred intervention or *cluster-optimized*, in which intervention assignments are optimized across the participant group). Participants receiving AI-optimized treatment received either group sessions, text messages from coaches, or automated messages each week. The three conditions achieved near-identical weight losses (~7%), but the AI conditions required only one-third the amount of coaching contact.[24] Although the effect size of condition on weight loss was near-zero (d=0.03), statistical non-inferiority could not be established in this underpowered pilot study.

Beyond this pilot study, no other trials to date have used AI to optimize obesity treatment, and only a few studies have utilized any form of AI to optimize behavioral coaching[23,25-27]. Thus, the primary aim of the trial described in this protocol will be to evaluate, in a sample of 336 adults with overweight/obesity, the hypothesis that an RL-based BWL program (BWL-AI) can produce non-inferior weight losses at 6 and 12 months to standard BWL treatment (BWL-S), but at lower costs (per participant and per kg weight lost). A secondary aim is to test the hypothesis that BWL-AI will be non-inferior to BWL-S in improving mechanistic target variables (calorie intake, physical activity). We will also examine whether AI intervention selections can be predicted by psychological/demographic variables thought to affect the need for higher-intensity treatment. Lastly, we will establish the feasibility and acceptability of BWL-AI, characterize the intervention selections made by the AI system, and evaluate whether AI intervention selections differ by treatment responder status.

## Methods

### Study Design

The trial was registered at ClinicalTrials.org (NCT05231824). Adults with overweight/obesity (*N*=336) will receive 12 months of treatment, divided into two phases. In Phase I, participants in both groups will receive one month of weekly, remote standard BWL group treatment. Phase I is immediately followed by Phase II, consisting of 11 months of remote intervention that will be either a continuation of standard, non-optimized BWL groups (BWL-S) or AI-optimized BWL (BWL-AI). In BWL-S, each participant will participate in weekly videoconference groups with an expert counselor. In BWL-AI, each participant will be assigned to one of four interventions each week based on continuously monitored digital data and using a cluster-optimized RL algorithm. Individual optimization was not included in this trial because cluster optimization produced equivalent results in our pilot, is more compatible with group intervention and allows for predictability of clinician time. Recruitment will occur in seven waves of 48 participants, with 24 participants (i.e., one “cluster”) randomized to each condition BWL-AI, BWL-S). See Figure 2 for the flow chart of study procedures.

### Phase I (Month 1)

Phase I will consist of 4 weekly, 90-minute group BWL sessions. The purposes of this phase are to provide foundational training in weight control skills, to facilitate a relationship between the participants and their counselors, and to establish a pre-randomization weight loss statistical control. The intervention will be adapted from gold standard BWL programs (e.g., the Diabetes Prevention Program; DPP) that yield 7-10% weight losses for most participants.[28,29] Intervention content will include nutritional education, problem solving, stimulus control, goal-setting, and self-monitoring skills. Each week, participants will receive a summary of this content through online modules, a specific behavioral goal, and a "check-in" form that reviews weekly progress.

Participants will be given weekly goals for moderate-to-vigorous physical activity (MVPA) and personalized weekly calorie goals. Participants will use a Fitbit wrist worn activity tracker (provided by the study) during all waking hours, weigh themselves daily using the Fitbit Aria wireless scale (provided), and use the Fitbit app's food tracking features to record everything they eat and drink.

### Phase II (Months 2-12)

**BWL-S—**In Phase II of the BWL-S condition, participants will continue receiving weekly 60-minute videoconference groups led by an expert counselor (who has an MS degree or higher in psychology, nutrition, or a related field, and expertise in BWL), as well as accompanying modules, assignments, and check-in forms. Groups will be more interactive than in Phase I, focusing on reviewing goal progress, problem solving, and learning and reviewing weight control strategies. Group size (i.e., 8 participants) and group membership will be consistent from week to week. Counselors will monitor, reference, and praise digital dietary and MVPA data to amplify beneficent surveillance and emotional support.[30-34]

**BWL-AI—**In Phase II, BWL-AI participants will be assigned one of four possible interventions each week: (1) an expert counselor-led 60-minute small group ($N$=8 BWL-AI participants from a given cluster) that will follow the same structure as the Phase II groups in BWL-S, (2) a 12-minute individual video call with the expert counselor, (3) a 12-minute individual video call with a paraprofessional (bachelor's degree, with a background in weight loss, diabetes or other health coaching, and who will also co-lead Phase I groups), or (4) an automated, tailored coaching message. Modules, assignments, and check-in forms will be assigned regardless of intervention.

**Automated Messages.:** The automated coaching messages will each consist of three components: (1) a summary of the participant's past-week patterns of calorie consumption, dietary self-monitoring, MVPA, and weight change during the past week; (2) tailored feedback on recent patterns of weight change (e.g., commenting on weight loss trajectory) and (3) tailored feedback on a single domain of behavioral adherence (calorie intake, dietary self-monitoring, self-weighing, or PA; see Figure 1). All feedback will be selected from a pre-generated message bank using an algorithm that ensures participants receive a balanced mix of praise and constructive feedback over the course of the program. To limit habituation to automated messages, participants will receive feedback on a different behavioral domain (e.g., calorie tracking versus PA) each week and will never receive the same exact message two times in a row. Automated messages will make use of evidence-based behavior change techniques for lifestyle modification such as providing feedback on monitored data,[35,36] social support (e.g., providing praise and emotional support),[33,37,38] and problem-solving (e.g., prompting participants to consider accuracy of recorded calorie totals)[30,39] Finally, to accommodate situations where participants feel overwhelmed and need to briefly pause their weight loss efforts, a "rescue mode" feature can be activated which will result in the participant receiving only encouraging messages without any suggestions for improvement (groups and individual calls will be unaffected). Messages will be transmitted via a dedicated mobile app. See Figure 3 for examples of automated messages.

**Portal.:** A custom-built web portal will retrieve weight, calorie, diet, and PA data from the Fitbit server via a secure token and will present MVPA, calorie intake (broken down by food item), and weight change data to counselors in a user-friendly, flexible graphical interface. The portal will also use Fitbit data to calculate a "reward score" for each intervention deployed to each participant, use the reward score to select an intervention, and notify participants and counselors of the intervention selections. The portal will also deploy the algorithm that creates automated messages and relays these to participants.

**Reward Score.:** At the end of each intervention week, an intervention-specific *reward score* will be calculated for each participant. The reward score is calculated by subtracting the "expected" weekly weight loss (for a typical participant, given time since the program started) from the actual (or imputed) weekly weight loss for each participant. Adjusting for expected weight loss is necessary to allow the algorithm (which compares weight losses within-person for interventions received at different times) to account for the fact that weight lost typically declines with intervention week. Expected weight losses will be determined through a curvilinear regression equation using data from a previous, large, remote weight loss trial we conducted.[1] When a participant's weekly weight loss is unavailable, weight loss/gain is imputed based on a regression equation calculated using our pilot data (see Pilot Phase). This equation takes into account the participant's last known weight, total weight loss to date, and the percentages of calorie goals met, days tracked dietary intake, and MVPA goal met in the past week (see Supplement). The selected equation performed the best (out of many options) in our post-hoc analyses of pilot data and assumes that (1) failure to weigh is associated with poor treatment response, (2) weight regain is proportional to total weight loss (due to weight suppression)[40], and (3) a participant who has disengaged will regain lost weight over the period of 1 year, conservatively doubling a previous estimate that treatment completers will regain 50% of their lost weight within 1 year.[41] The *average reward score* for each intervention continuously updates according to a decay function (i.e., a recent response to the given intervention counts more than a distant response). Importantly, the reward score calculation anticipates and reflects that individual participants will have periods of self-monitoring non-compliance and/or non-engagement in treatment, and the AI system optimizes intervention selection to remediate these periods. Non-engagement is

[1]The following equation will be used to determine expected weight loss: Expected Weight Loss = $1.08*\text{Week}^{-0.341}$, where Week 1-4 are treated as a single week due to the distinct nature of Phase I from Phase II (i.e., Weeks 1-4 are coded as Week 1, Week 5 is coded as Week 2, etc.).

incorporated indirectly, such that a failure to engage (e.g., not answering coach phone calls) will result in that intervention having no positive effect on participant outcomes and thus being selected less often.

**Use of Cluster Optimization (CO).:** Optimization is based on the “UCB1” formula, which assigned two scores for each intervention and each participant: an exploitation score (average reward score) and an exploration score (a radical function that increases inversely to the proportion of the time that the intervention has been assigned to the participant; see Supplement).[42,43] Thus, the formula balances exploitation (favoring interventions that produced the best response for each person) and exploration (favoring interventions that have not been assigned enough to a person to confidently estimate his/her response to it). For each “cluster” of 24 AI participants (who are in the same recruitment wave, share clinician time and whose assignments must be optimized together), the CO algorithm chooses the optimal combination of all 5,892,355,924[2] possible intervention assignments that meet a specified constraint (in this case: 60 or 90 minutes of clinician availability).[44] CO does not necessarily assign the optimal intervention to each participant; instead, it makes use of the available clinician time in an optimal manner. For example, participants with negligibly worse responses to automated messages relative to other interventions may be assigned to automated messages to leave room in groups for participants who have far better responses to groups than to other interventions.

**Communication with Participants.:** To provide participants with advance notice, intervention assignments will be communicated weekly, via the mobile app, on the fifth day of each intervention week. To allow for the UCB1 score to be calculated two days early, on this day, a temporary (“prorated”) reward score (later replaced) will be calculated.

**Pilot Phase.:** Adults with overweight/obesity (*N*=32) were recruited in two waves and received 2 weeks of remote BWL treatment sessions followed by 8 weeks of remote AI optimized (BWL-AI) intervention. Qualitative and quantitative data on participant satisfaction, engagement, and feedback were collected. Participants rated automated messages for clarity and helpfulness, and messages receiving lower ratings were modified accordingly. Following the pilot phase, we refined: (1) the language used to recruit for the study, (2) the language used to describe the study to interested participants, (3) the automated coaching algorithms and messages, (4) the web portal used by clinicians and supervisors, and (5) the mobile app used by participants.

## Counselor Training and Supervision

While expert counselors will complete a brief BWL training, paraprofessionals will complete intensive training (15 hours; didactic and experiential) in BWL and effective coaching (in line with prior studies[17,45,46]). All counselors will receive weekly clinical group supervision. Group and individual sessions will be video recorded, and evaluators will

[2]There are two combinations of intervention assignmnent in an AI group of 24 participants (i.e., 8 in group, 6 calls, 10 messages, and 0 in group, 12 calls and 12 messages). The number of combinations is thus calculated using the binomial coefficient, “n choose k” which represents the number of ways to choose an (unordered) subset of k elements from a fixed set of n elements, i.e., (24 choose 8) × (16 choose 6) + (24 choose 12).

independently rate treatment competence and fidelity for 25% of sessions. Shortcomings will be addressed immediately. Assignment to conditions will be balanced across expert counselors.

## Participants

Inclusion criteria are: BMI27-50 kg/m$^2$; age 18-70 years; completion of baseline assessment tasks; ability to engage in PA (i.e., can walk at least 2 blocks without stopping for rest); can provide consent to contact personal physician if necessary for clearance or consultation; willing to use Apple or Android-based smartphone (a smartphone and/or data plan will be provided by the study if needed). Exclusion criteria are as follows: medical condition (e.g., cancer, full-threshold eating disorders) that may pose a risk to the participant during intervention or cause a change in weight; currently pregnant, breastfeeding, or planning a pregnancy in the next 12 months; recently began or changed the dosage of medication that can significantly influence weight; history of bariatric surgery; weight loss of ≥ 5% in the previous 6 months.

Participants will be screened by phone for preliminary eligibility and interest, then invited to a remote orientation session where they will receive detailed information about the study and can read and sign the consent form if still interested. Full eligibility will be verified through a subsequent semi-structured interview before the participant can enroll.

## Measures

Assessments will take place at 0-, 1-, 6- and 12-month intervals, and participants will be compensated for completing them.

**Primary Outcome: Weight.—**At each assessment, weight will be measured using the Fitbit Aria wireless scale (which is comparable in reliability to high-precision medical scales for assessing weight change over time[47]), taking the average of 5 consecutive daily weights for each timepoint, and removing any errant weights (i.e., >1 kg change in 1 day).

**Secondary Outcomes:** Minutes of MVPA will be measured via the *Fitbit Inspire 2*, a consumer-grade wrist-worn activity tracker which has superior compliance and close-to-equivalent accuracy to a research-grade accelerometer[48], over the course of seven days. Each participant's 7-day average calorie intake as derived from the Fitbit app's food log will be used as a secondary outcome at each assessment point.

**Potential Predictors of Intervention Selection:** Several variables posited to predict intervention selection will be measured at baseline and 1-month assessment: 1) self-regulation capacity, using Brief Self-Control Scale [49], 2) autonomous motivation using the Treatment Self-Regulation Questionnaire[50], 3) depressive symptoms, using the Center for Epidemiologic Studies Depression Scale,[51] 4) binge eating, using the Eating Disorders Examination,[52,53], and 5) food addiction using the Modified Yale Food Addiction Scale 2.0[54].

**Cost Data.—**Program costs will be recorded as intervention costs and participant costs. Intervention costs, measured per person based on intervention assignment, include all the costs of maintaining the AI system, which includes the costs of training and developing all materials provided across interventions. Participant costs, based on average wage rates of participants, will be measured by recording all time spent on intervention activities, such as time spent in treatment sessions. Further cost differences based on potential use of health services will also be recorded and converted into cost figures, referencing typical prices for various services (e.g., outpatient medical visit).

**Acceptability.—**To assess acceptability, participants will be asked to rate satisfaction with and perceived effectiveness of the program. Counselors will rate effectiveness and ease of use.

## Statistical Analyses

Descriptive statistics and exploratory graphing will be generated for all variables of interest measured at all time points. Data summaries will be produced both for the combined sample and separately by treatment arm. Variables will be transformed, if necessary, using a Box-cox power transformation. Key baseline variables that differ by treatment arm will be considered for use as covariates in the analyses below.

**Non-Inferiority Analysis—**To examine whether BWL-AI weight losses at 6 and 12 months are noninferior to BWL-S, we will model the pattern of weight change over time using three-level multilevel models[55-57] with repeated assessments over time nested within individuals and within randomized clusters to account for hierarchical data structure. The cross-level interaction between time and treatment will determine the effect of treatment condition on weight loss. Restricted maximum likelihood will be used to estimate model parameters and evaluate random effects. The basic formation of multilevel models considers time as linear. Higher-order time effects will be examined based on model selection criterion such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). With the fitted multilevel model structure, statistical contrasts will be performed at 6 and 12 months with the noninferiority margin set to 1% weight loss.[58,59] This criterion was chosen because of evidence that weight changes as modest as 2-3% have clinical significance.[60] To examine whether BWL-AI improvements in secondary outcomes are non-inferior to BWL-S, these same non-inferiority analyses will be repeated using calorie intake and MVPA as outcome variables.

**Cost Analysis—**The cost analysis follows adopted guidelines[61] and takes a societal perspective by including both the cost to deliver the intervention and to participate in it (e.g., cost of resources to provide the information, healthcare and productivity costs)[62,63], as previously described. A micro-costing approach will be used to estimate the costs of materials (e.g., Fitbit wrist-worn tracker and scale); paraprofessional and expert counselor pay for time spent training for, preparing, and delivering the intervention (hourly pay plus fringe); and costs for participants (post-tax wage rate and fringe benefits to value the time spent participating in the intervention). Additional costs for developing and maintaining the AI system, and any other software costs associated with automated text messaging or optimization will be included. Costs for adapting the system to a new setting will also be estimated. BWL-AI and BWL-S will be compared in terms of the cost per participant and per kg of lost weight at 12 months using ANCOVA.

**Feasibility and Acceptability—**We will assess the feasibility and acceptability of the AI system using the following benchmarks: (a) recruitment success: enrollment of 336 participants; (b) study retention: >80% retention through all assessments; (c) counselor satisfaction: >85% of the counselors report the AI system and portal is easy to use and effective; (d) participant satisfaction: >80% of AI participants express high satisfaction with treatment.

**Predictors of Intervention Selection—**To examine if intervention selections can be predicted by depression, binge eating, food addiction, motivation, self-regulation, sex, race, and responder status (<3% vs. ≥3% weight loss), we will use binary and multinomial logistic regression models in which predictor variables predict the frequency of each intervention selection for each participant.

**Attrition—**Likelihood-based estimation methods and multiple imputation models will be used to handle missing data.[64] If the missingness mechanism is related to the missing outcome itself, we will use sensitivity analyses to explore how robust our findings are with respect to a range of assumptions regarding missing data.

**Power Analyses—**Using the method described by Raudenbush[65-67] and implemented using the software Optimal Design, power calculations were made for this multilevel model structure. With the predefined noninferiority margin of 1% weight loss, standard deviations estimated from our pilot study ReLearn, and an estimated 17.5% of variance in 1-year weight loss explained by 4-week weight losses based on our most recent obesity treatment trial, a sample size of 244 is required for 80% power based on an alpha level of .05 and four assessment points, assuming that the ratio of the variability of the level-1 coefficient to the variability of the level-1 residual is at least one. To conservatively allow for ~25% attrition, we have proposed $N = 336$. For ANCOVA, the required sample size is 128 to achieve 80% power with a medium effect size and an alpha level of .05. For logistic regression, a sample of 208 is required for 80% power to detect an odds ratio of 1.5 using an alpha level of .05.[68,69] Thus, the study will be sufficiently powered for all aims with the proposed sample size of 336.

## Discussion

Gold standard treatments for obesity such as BWL can produce clinically significant weight loss (7-10%) but are expensive and difficult to disseminate[3-13]. A more scalable approach would be to deliver lower-intensity (and lower-cost) treatments to individuals who benefit from these interventions while reserving full-intensity (high-cost) treatments for individuals who require additional support. An ideal method for allocating resources in this way is the AI technique of RL, which can predict the most effective intervention for a participant at any given time during treatment within a set of resource constraints. This study represents the first full-scale trial of an AI-based system for optimizing delivery of weight loss treatment, and examines efficacy, cost-effectiveness, moderators, feasibility, and acceptability.

Whereas most obesity treatment research is focused on enhancing efficacy, the current trial has an innovative focus on reducing costs without sacrificing outcomes by efficiently allocating a constrained set of resources.[23,25,26] RL-based AI algorithms have previously been utilized to optimize coaching within several behavior domains, including digital messaging applications to promote physical activity[25], and oral hygiene[23] and court hearing attendance,[26] but not weight loss. (Of note, although commercial applications such as Noom[70], Omada[71], and HealthifyMe[72] use AI to provide personalized behavioral suggestions, no prior work to our knowledge has utilized AI to individually tailor the intensity level of treatment). A particularly innovative aspect of the proposed AI approach is that unlike stepped care[21,73,74], which optimizes treatment intensity at one or two pre-established points, an RL algorithm can re-optimize treatment continuously and in a fully automated, highly scalable fashion. The AI system will also select interventions factoring both cost and relative effectiveness of the different intervention options available, rather than simply changing treatment intensity for an individual who is not losing weight to the extent expected. Thus, under the proposed AI system, participants will always receive the intervention that appears to benefit them the most (relative to all other intervention options), which also prevents problematic withdrawal of resources from individuals who show suboptimal initial treatment responses. Finally, this study will also be among the first to 1) optimize the use of lower-cost paraprofessionals, 2) use AI to optimize counselor time and training level between and within participants, and 3) evaluate predictors of AI intervention selection (thus aiding the development of future AI systems that can predict differential intervention response early in treatment).

One challenge faced in designing the current trial was selecting an optimal design for the BWL-S comparison group. Because the AI system selects weekly interventions at the individual participant level, we initially considered using one-on-one coaching calls, which represent the highest-intensity form of treatment possible for an individual, for the BWL-S condition. However, we ultimately decided to use group counseling for the comparison condition. Group counseling is the most efficient form of standard BWL[75], and is therefore the most stringent comparison against AI's cost-effectiveness. Another challenge was deciding which treatment options should be available for the AI system to select each week. We ultimately selected four options that vary in cost and intensity and that are in common usage (i.e., automated message, paraprofessional-delivered call, MS-expert group, and MS-expert call). Although other options would have been possible (e.g., paraprofessional-led group), we felt that these were less commonly used, and recognized it was important to limit the number of options to allow the AI system to better "learn" which intervention produces the best response for each participant given the limited number of samples (i.e., 52).

A significant limitation of this study is that findings will not inform how an AI system could be implemented in an actual healthcare system (e.g., hospital, medical system, insurance company) and will only provide insight into weight loss efficacy of this system within a controlled research setting. Future trials will be needed to evaluate feasibility and identify challenges associated with integrating AI optimization algorithms systems into real-world healthcare settings. For example, the AI system being evaluated in this study requires that patient appointments vary in duration from week to week, which could be challenging to implement depending on the insurance reimbursement structure used. However, an advantage of the proposed AI system in the context of a typical healthcare setting is that it provides constraints for counselor time. Relatedly, another limitation specific to the proposed AI approach is the dependence on computing systems and algorithms that may not be feasible to implement in some settings. A third limitation of the current study is the generalizability of results, given that participants in the AI treatment must be willing to be assigned to a different intervention each week.

In sum, the current study has potential to improve scalability of effective obesity treatment by demonstrating that an AI-driven approach to treatment selection can produce equivalent weight losses to gold standard approaches at a lower cost. Such evidence could help to make effective treatment more accessible to many millions of individuals with obesity who are currently without access to high-quality care. Lastly, we hope that the findings of this trial will inspire additional research focused on AI-based treatment approaches for weight loss, which may aid in successfully curtailing the ongoing epidemic of overweight and obesity.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

## Source(s) of support:

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**Figure 1.**

Application of reinforcement learning in the ReLearn Project

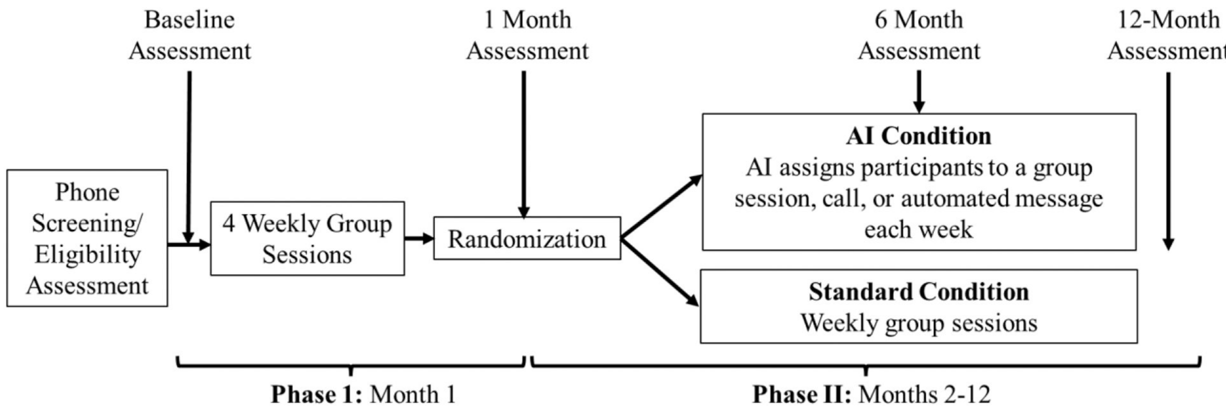


**Figure 2.**
Flow chart of study procedures

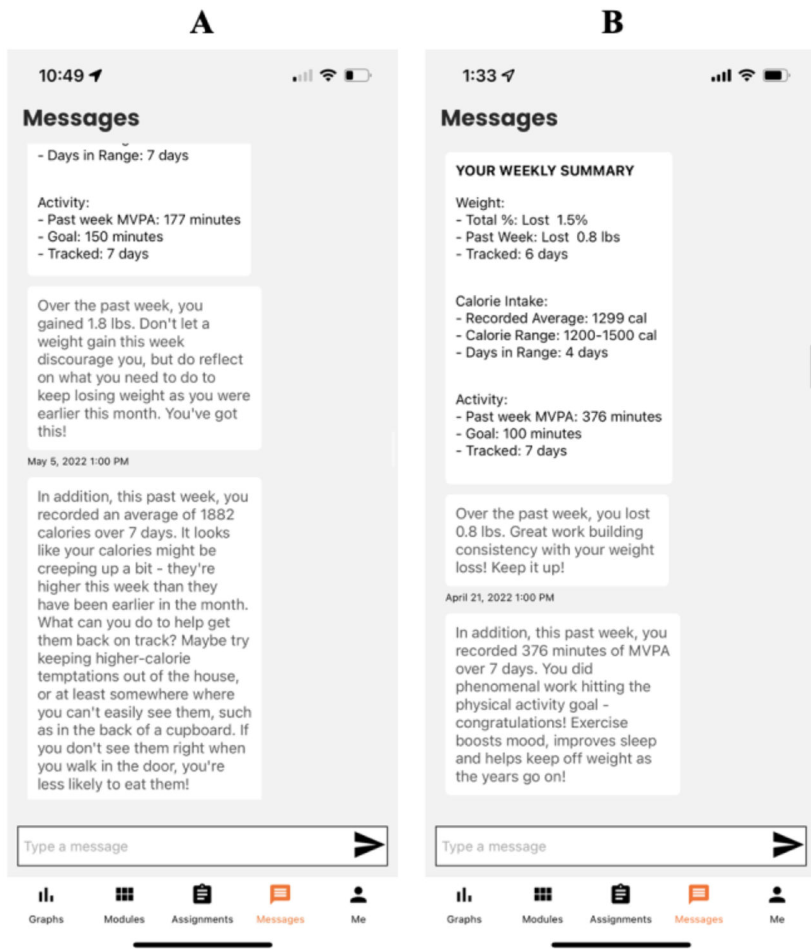


**Figure 3.**

Examples of in-app automated messages

**Table 1.**

Macro-level view of resource allocations under various scenarios.

| **Scenario** | **Macro-level implication** | **Potential Optimization** |
|---|---|---|
| Low-need participants receiving high-intensity intervention | Wasted resource that should be redirected | Reduce intensity, redirect resources to those who would benefit |
| High-need participants receiving low-intensity intervention | Subset of participants receive no benefit | Direct resources to this subset |
| Nonresponsive participants receive high-intensity intervention | Wasted resource that should be redirected | Reduce intensity, redirect resources to those who would benefit |
| Participants who were low-need and transition to high-need continue to receive low-intensity interventions | Previous benefit is reversed, and resource is wasted | Increase intensity |
| Participants who were high-need and transition to low-need continue to receive high-intensity interventions | Wasted resource that should be redirected | Reduce intensity, redirect resources to those who would benefit |