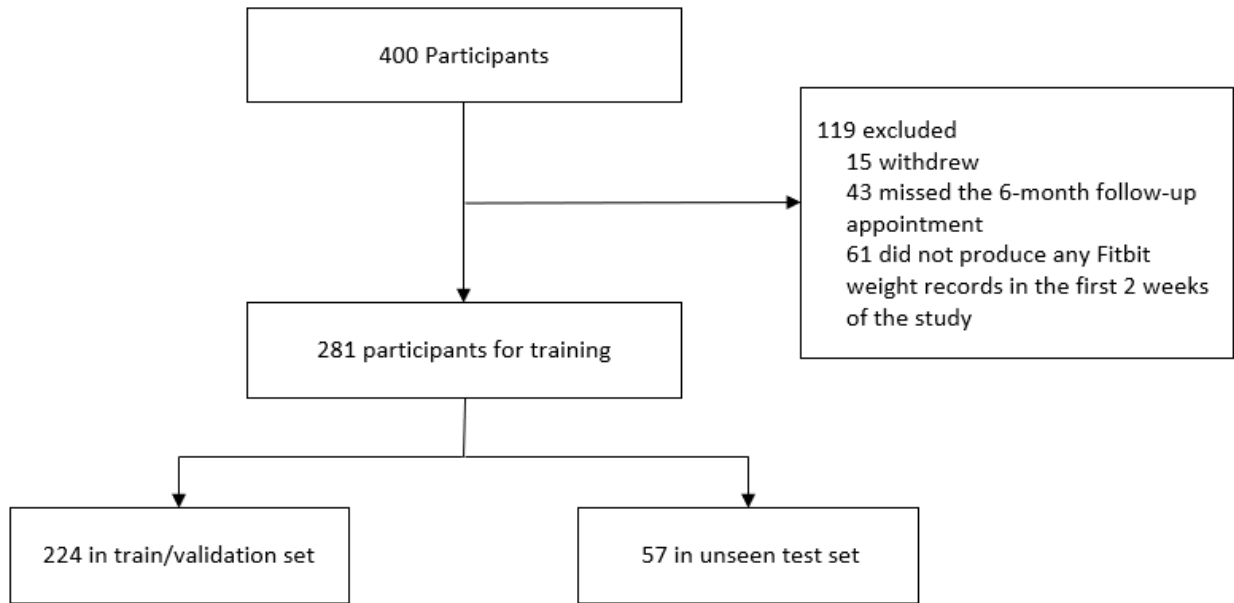
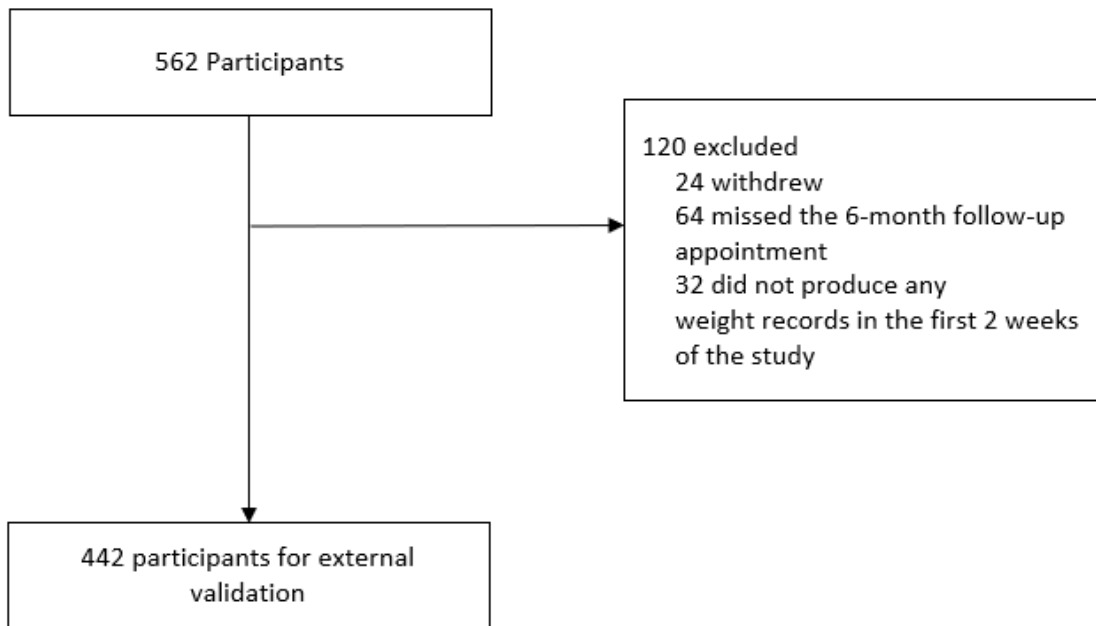


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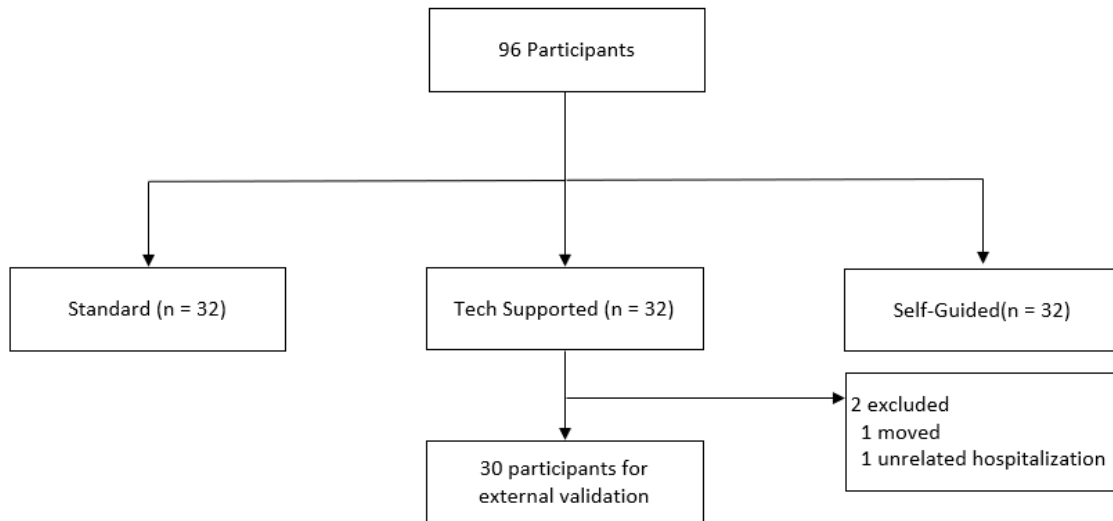
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Supplementary Figure 1: Study profile for SMART study The figure provides a visual representation of the number of participants in the SMART Weight Management Study. It illustrates the total number of study participants, the count of individuals excluded from our analysis, and the overall number of participants considered in our analytical assessment.



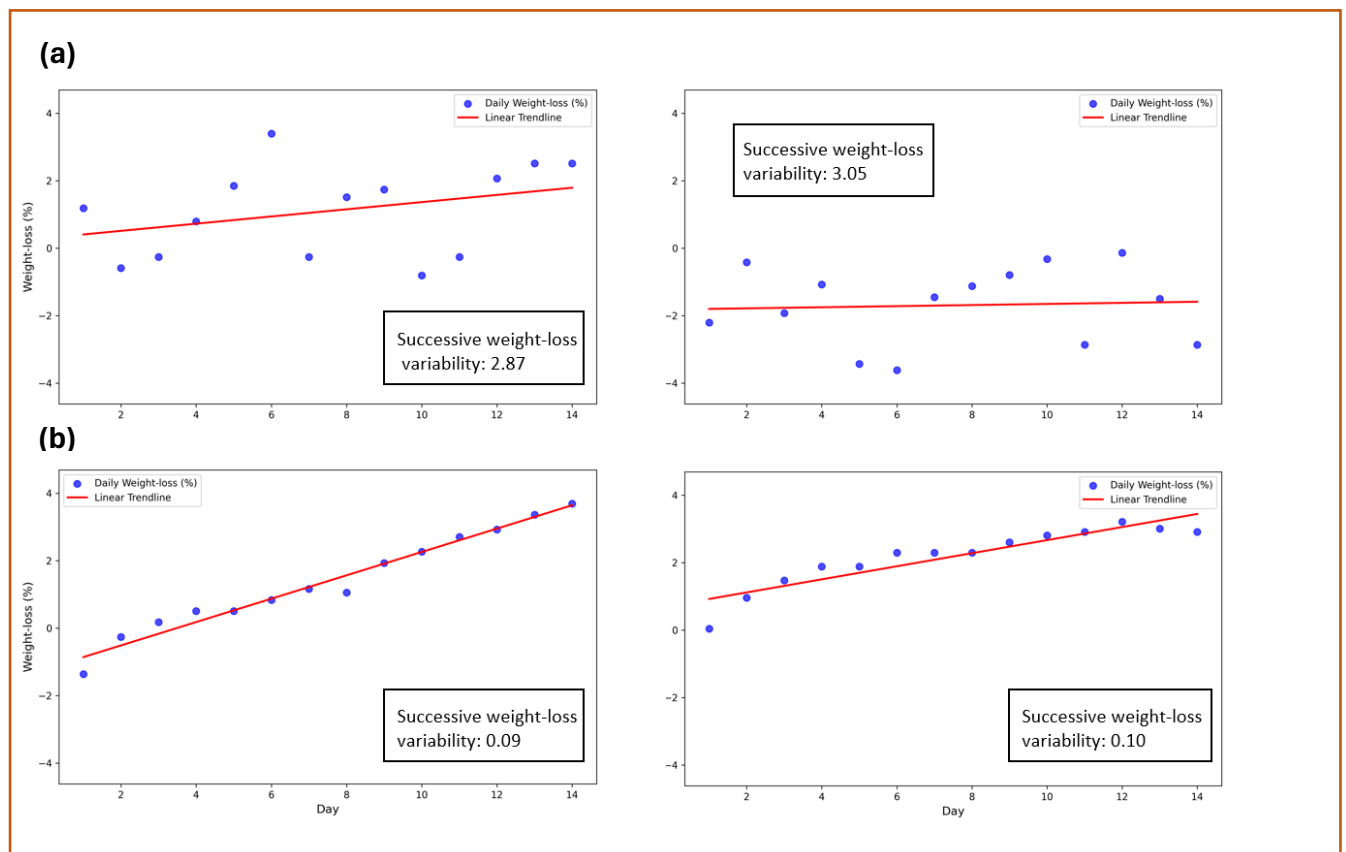
Supplementary Figure 2: Study profile for Opt-IN study. The figure provides a visual representation of the number of participants in the Opt-IN Weight Management Study. It illustrates the total number of study participants, the count of individuals excluded from our analysis, and the overall number of participants considered in our analytical assessment.



Supplementary Figure 3: Study profile for ENGAGED study

The figure provides a visual representation of the number of participants in the ENGAGED Weight Management Study. It illustrates the total number of study participants, the count of individuals excluded from our analysis, and the overall number of participants considered in our analytical assessment.

Supplementary Figure 4



Supplementary Figure 4: Examples of individuals with high and low weight loss variability. This figure presents the variation in weight change over 14 days from baseline weight for four participants. Successive weight-loss variability was calculated based on the daily weight loss percentages (in blue). To better visualize the overall trend and highlight the variation in weight loss over time, a red linear trendline is superimposed on each plot. This allows for a clearer comparison of weight-loss consistency among the participants, distinguishing those with high variability from those with low variability. (A) Two individuals with high weight variability are shown, calculated using the proposed successive weight loss variability method. (B) Two individuals with low weight loss variability are presented.

Weight Variability Measures	Formal Operational Definition	Derivation	Domain/Application	References
Coefficient of Variation	The standard deviation of the observed records over the average of the observed records	$CV = \frac{\sigma}{\mu}$ where: μ = observed records' mean, σ = observed records' standard deviation	All-cause mortality, Type 2 diabetes	Nam et al., ¹ Okada et al. ²
Mean Successive Variability	The mean absolute difference between successive weight records	$ASV = \frac{1}{n} \sum_{i=1}^{n-1} y_i - y_{i+1} $ where: n = the number of records, y_i = observed record	Coronary disease, Diabetes, Heart failure with preserved ejection fraction (HFpEF)	Banglore et al., ³ Rhee et al., ⁴ Li et al. ⁵
Root Mean Squared Error	The square root of the average of the squared residuals from linear regression method	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$ where: y_i = observed record, \hat{y}_i = fitted record, n = number of records	Long-term weight-loss success, Cardiovascular, All-cause mortality	Benson et al., ⁶ Cologne et al., ⁷ Dyer et al. ⁸
Non-linear Mean Deviation	The average of the absolute residuals error from LOESS regression method	$NLMD = \frac{1}{n} \sum_{i=1}^n y_i - \hat{y}_i $ where: y_i = observed record, \hat{y}_i = fitted record	Weight-loss maintenance	Turicchi et al. ⁹

Supplementary Table 1: Descriptions of Body Weight Variability Operational Definitions in Difference Studies

ML Model	Sensitivity	Specificity	F1-score (6-month weight-loss success)	F1-score (suboptimal 6-month weight-loss)	F1 weighted	ROC-AUC	Balanced Accuracy
k-NN	0.364	0.714	0.400	0.676	0.569	0.519	0.539
Logistic Regression	0.318	0.914	0.438	0.780	0.648	0.684	0.616
Naïve Bayes	0.455	0.743	0.488	0.712	0.626	0.701	0.599
Random Forest	0.409	0.714	0.439	0.685	0.590	0.652	0.562
SVM	0.273	0.714	0.316	0.658	0.526	0.497	0.494
Gradient Boosting	0.227	0.886	0.323	0.747	0.583	0.713	0.556
Mean (STD)	0.341 (0.085)	0.781 (0.093)	0.401 (0.069)	0.710 (0.046)	0.590 (0.043)	0.628 (0.095)	0.561 (0.044)

Supplementary Table 2: Performance of ML Models at Baseline

We conducted training and testing of both discriminative and generative models, utilizing static features such as psychological and demographic attributes collected at the baseline. This table provides an overview of the baseline results. Notably, the Logistic Regression algorithm demonstrated F1 weighted scores of 64.8% and balanced accuracy of 61.6%. In general, the machine learning models trained at baseline exhibited an average F1 weighted score of 59.0% with a standard deviation of 4.3%.

ML Model	Sensitivity	Specificity	F1-score (6-month weight-loss success)	F1-score (suboptimal 6-month weight-loss)	F1 weighted	ROC-AUC	Balanced Accuracy
k-NN	0.318	0.914	0.438	0.780	0.648	0.741	0.616
Logistic Regression	0.545	0.886	0.632	0.816	0.745	0.795	0.716
Naïve Bayes	0.773	0.743	0.708	0.788	0.757	0.842	0.758
Random Forest	0.818	0.714	0.720	0.781	0.758	0.845	0.766
SVM	0.318	0.714	0.359	0.667	0.548	0.531	0.516
Gradient Boosting	0.409	0.886	0.514	0.785	0.680	0.808	0.647
Mean (STD)	0.530 (0.222)	0.810 (0.095)	0.562 (0.148)	0.770 (0.052)	0.689 (0.083)	0.760 (0.118)	0.670 (0.096)

Supplementary Table 3: Performance of ML Models by Week 2

In this table, we present the predictive performance of our machine learning models, utilizing both dynamic features gathered during the two-week treatment period and static features obtained at baseline. The Random Forest model stands out with the highest F1 weighted score of 75.8% and balanced accuracy of 76.6%. On average, we attain an F1 weighted score of 68.9% with a standard deviation of 8.3% implying a 9.9% improvement overall using the dynamic features obtained from the two-week weight loss trajectory.

Variable	Feature Description
<i>Statistical Features</i>	
Mean	Average weight loss from a two-week weight trajectory
Variance	Variance of the weight loss from a two-week weight trajectory
Median	Median of the weight loss from a two-week weight trajectory
Maximum	Maximum weight loss from a two-week weight trajectory
Minimum	Minimum weight loss from a two-week weight trajectory
75 th Percentile	75 th percentile weight loss from a two-week weight trajectory
25 th Percentile	25 th percentile weight loss from a two-week weight trajectory
Range	Range of weight loss from a two-week weight trajectory
Inter-quartile range	Distance between 75 th percentile and 25 th percentile
Slope	Slope obtained from the best-fitted regression line for the two-week weight trajectory
Intercept	Intercept obtained from the best-fitted regression line for the two-week weight trajectory
Zero-crossing	Number of times in change of sign (e.g., positive to negative) in the mean-centered two-week weight loss trajectory
Kurtosis	A measure to calculate whether the two-week weight loss trajectory is heavy-tailed or light-tailed
Skewness	A measure to calculate the skewness of the weight loss trajectory
Weight loss on the 14 th day (%)	The percent of weight loss on the 14 th day
Weight loss on the 7 th day (%)	The percent of weight loss on the 7 th day
Sparsity-adjusted successive weight variability (SASWV)	As described in the main body of the paper
<i>Baseline Features</i>	
Self-efficacy Score (diet)	As described in Pfammatter et al. ¹⁰
Self-efficacy Score (exercise)	As described in Pfammatter et al. ¹⁰
Sex	Sex
Race/ethnicity	Combined race and ethnicity variable
Age	Age
Height	Height
Baseline weight (lb)	Weight measured in the beginning of the study

Supplementary Table 4: Feature Description Table

In this table, we provide a detailed description of the features utilized in the machine learning models, encompassing both baseline features and statistical characteristics.

Supplementary Note 1

Stratified Splitting and Model Evaluation

To maintain an unbiased modeling approach, we randomly split the data into train, validation, and test sets, stratified by sex, race/ethnicity, and the outcome variable (weight loss success) to ensure diversity within each set while avoiding cross-contamination. We repeated this 60/20/20 split 15 times using different random states, with each iteration selecting distinct samples for the train, validation, and test sets while preserving the same stratification. We then compared the results (with a fixed random state) to the 95% confidence interval range for the F1 weighted score. We observed that the results consistently fell within this confidence interval, confirming that the F1 weighted score of 75.7% was within the confidence interval range (95% CI, 74.8%-77.1%).

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