Two-Year Results of Think Health! *¡Vive Saludable!* - A Primary Care Weight Management Trial

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SUPPORTING INFORMATION

Full Description of Statistical Analyses

Total follow-up time was calculated by subtracting date of randomization from the date of the last available weight measurement (i.e., final measurement visit or latest treatment or medical record weight before month 24, or the date of withdrawal where applicable (n=26)). During the interim data analysis, we determined the acceptability of using weight measurements from treatment visits and medical records by comparing 1-year weights from these sources for participants who had a weight measurement in the same month by a research staff member (1). Intraperson differences were small and not biased toward either source and mean differences between Basic (0.04 kg) and Basic Plus (0.14 kg) were similar and very small.

For body weight (primary outcome), we fit an array of potential models that allowed for complex trajectories of change over time, using all available weight measurements from any source, and compared them by the Akaike Information Criteria (AIC), a measure of fit that penalizes for added model complexity (2). All models were fit by linear mixed-effects regression models with randomization stratification variables (primary care practice site, age group, and gender) as covariates and random intercepts for individuals and random slopes for time. The best fitting model used cubic splines with four knots, at months 8, 12, 16 and 20 months, assuming linear trends before 8 months and after 20 months but cubic polynomials between 8 and 20 months (3). Difference in weight change by treatment group was estimated by comparing the predicted differences over time, 24 months vs 0 months, using model-based expected values. With this approach to estimation, the analysis could use all patient weight measures regardless of the actual visit date and did not require an *ad hoc* method of rounding dates to the nearest month or quarter. Percent weight change was also estimated from model-based predicted values for individual patients. Sensitivity of the model to loss to follow up was assessed by refitting the model with adjustment for baseline predictors of having no weight measurement available from any source within the two months prior to the expected end of follow-up. A graphical representation of the model was prepared by plotting observed raw values using a locally weighted linear regression smoother (lowess) compared to the model-based predicted values. Percent weight change was also estimated from model-based predicted values for individual patients. Sensitivity of the model to loss to follow up was assessed by refitting the model with adjustment for baseline predictors of “dropout”, defined as having no weight measurement available from any source within the two months prior to the expected end of follow-up. Models for secondary outcomes (change in blood pressure and waist circumference) followed the same form as those for weight change. Given that there were up to three repeated measures, the best fitting model was a linear model.

Treatment-visit attendance was used as a measure of dose, i.e., observed minus expected or the ratio of observed to expected. We implemented an instrumental variable method outlined by Nagelkerke et al (4) and Small et al (5) for longitudinal data to examine the sensitivity of the primary result to lack of attendance. In brief, this method uses randomized treatment assignment as an instrument and then adjusts for confounding arising out of unobserved variables such as those that might be associated with the outcome and with the decision to comply with the Basic Plus treatment schedule. The observed versus expected treatment visits attendance measures were categorized as above or below 30%, 40%, or 50% of expected as of any given visit. The resulting mixed-effects model then included the binary variable for attendance as the exposure of interest, the residual of expected and actual attendance as a key adjustment for confounding, baseline covariates, and cubic splines as previously specified. Random effects included patients and the three spline time segments. These models estimated the effect of attendance at Basic Plus visits on mean weight change assuming the specified threshold of attendance among those assigned to coaching visits versus having no access to coaching visits (i.e., Basic).

We explored the association between the number of coaching sessions attended and overall weight change considering only patients randomized to Basic Plus. We fit a linear mixed-effects model, like that described for the primary outcome, with cubic splines for the trend over time, the interaction of number of coaching sessions and time as the factor of interest. The model adjusted for all baseline characteristics as potential confounders, namely clinical site, race/ethnicity, age group, education, gender, employment status, marital status, sole caregiver, number of persons living at home, mode of transportation, perceived stress, life changes, as separate variables for financial, work, home, personal or other rather than an overall count or score), smoking status, drinking status, self-rated health, number of previous weight loss programs, food habits, high blood pressure, blood pressure medication, BMI, number of comorbidities, physician recommendation regarding the need for exercise limitations, and physical activity. The linear contrast of the time by coaching sessions interaction represented the rate at which average weight change from baseline varies with the number of sessions attended. A second model considered the percent (rather than number) of coaching sessions attended by dividing the number of sessions attended by the expected number of sessions attended. In addition, to investigate baseline factors that might predict the number of coaching visits attended, we fit a generalized linear model with a negative binomial distribution and log link to account for overdispersion in the number of coaching sessions attended. We repeated the analysis to consider the percent of coaching sessions attended by adding an offset term to the negative binomial model for the expected number of sessions attended. All analyses were performed using SAS (v 9.4) and Stata (v14.2).

References

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