**Online-Only Supplement**

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**eMethods – Supplementary details to manuscript methods**

**Study Design**

*Analytical method selection*

Biometric and demographic data from April 2015 to May 2018 were extracted retrospectively for children in the Denver Health (DH) Federally Qualified Health Center (FQHC). Initial MEND+ sessions took place in April 2016 and were subsequently offered at several intervals throughout the study period. Children entered and exited the DH FQHC pediatric patient population at various time periods, and MEND+ Attendees also began and ended their curriculum enrollment at different time points.

Given the variable time points of children included in the analysis, mixed effects models were selected as the analytical method of choice. Mixed-effects models take into account both fixed and random effects, and accounts for correlated, uneven spacing of repeated measurements within study subjects for all measured data, rather than just a few select data points 1. Mixed-effects models also take time into account, and thus it is not necessary to have equal amounts of time in children across a cohort. Therefore, the use of mixed-effects models allowed for the examination of differences in the rate of body mass index (BMI) and blood pressure (BP) change by comparing the rate of change before and after participation in the intervention among Attendees. In addition, mixed-effects models accounted for the starting value of BMI and BP, as this is already incorporated into the model. Overall, mixed-effects modeling allows for the analysis of within group changes over time. Mixed-effects modeling may also compare across groups, although this was not done in this study as there was no specific control group. Rather, separate mixed-effects models were run for each analytical group and then compared. We did not include the Referred or Eligible children as control groups in the same nested mixed effects regression models with the MEND+ Attendees due to unbalanced panel data. Doing so would have introduced additional bias as MEND+ Attendees had frequent BMI measurements due to weekly MEND+ clinic visits, compared to Referred and Eligible children whose frequency of measurements in real world EHR data were determined by clinical need for healthcare visits.

Although 1:n matching was considered as an analytical method, this approach is not as well suited for this retrospective cohort study. There were varying time points of engagement with the exposure of MEND+ participation, which itself was characterized by frequent biometric data measurement during curriculum enrollment. In addition, 1:n matching would utilize only some of the available data from a fraction of the total population. Mixed-effects models are more robust and allow for all data points contained within the study period to be analyzed.

**Outcome measures**

*Percent (%) of the 95th percentile*

There are well documented limitations of using BMI z-score (BMIz) as a measure for quantifying changes in body mass index among children who participate in weight management interventions 2-5. Use of BMIz as a metric can make it difficult to detect meaningful changes due to the statistical properties and limitations of BMIz 6. This is particularly true for children with severe obesity, defined as a BMI that is ≥120% of the BMI value at the age- and sex- specific 95th percentile based on CDC growth charts 3. Using change in BMIz as a primary outcome to measure the impact of a pediatric weight management intervention (PWMI) could result in erroneous conclusions, particularly if participants have severe obesity. To avoid the statistical limitations of BMIz, one can characterize longitudinal change in BMI using the metric of ‘BMI % of the 95th percentile’ (%BMIp95), which can be applied to all children in an intervention study, across a wide range of BMI values.

**Covariates**

*MEND+ Sessions*

The complete MEND 7-13 curriculum is 10 weeks long, with two sessions per week. Therefore, MEND+ consists of a total of 20 sessions. However, medical visits with a clinician were only incorporated into one of the two sessions each week. This integrated medical visit was not done consistently during the first or second session each week but could occur on either day. During these medical visits, clinical measures of height, weight, and blood pressure were taken and entered into the EHR. Therefore, although 20 sessions were part of the curriculum, only 10 sessions had documented clinical data. The MEND+ program did not document attendance for the 10 non-clinical sessions during the other day of the week. Therefore, the number of medical visits recorded in the EHR is not an absolute proxy for overall MEND+ session attendance. Some children may have come during the medical visit day and not the other day of the week, or vice versa. As biometric data were only obtained on the medical visit day, this is the only day for which data are present in the EHR.

**Data cleaning**

The table below details the steps of cleaning the anthropometric data obtained from the EHR. After application of the algorithm developed by Daymont et al. 7 to remove common height and weight measurement errors, the Lowess (locally weighted scatterplot smoothing) method, specifically Friedman’s Super Smoother package 8,9, was applied to identify additional erroneous body weight observations not flagged by the automated algorithm. Finally, the CDC SAS Macro 10 was used to calculate %BMIp95.

**eTable. Cleaning of height and weight electronic health record data of Denver Federally Qualified Health Center pediatric patients with BMI ≥85th percentile, 2015–2018.**

|  |  |  |
| --- | --- | --- |
|  | **Heights** | **Weights** |
| **Number of observations in initial dataset** | 104,379 | 104,368 |
|  | Daymonta cleaning algorithm applied | |
| **Duplicate values dropped** | - 620 | - 618 |
|  | 103,759 | 103,750 |
| **Heights without associated weights dropped** | - 2 |  |
|  | 103,757 | 103,750 |
| **Other erroneous values dropped** | - 1,517 | - 212 |
|  | 102,240 | 103,538 |
|  |  | Lowessb method applied |
| **Erroneous weights dropped** |  | - 9 |
|  | 102,240 | 103,529 |
|  | Data sets merged | |
| **Data rows with both height and weights** | 102,074 | |
|  | CDC Growth Chart Macroc applied | |
| **Children < 2 years old dropped** | - 873 | |
| **Final number of height and weight observations** | 101,201  (associated with 21,408 unique individuals) | |

aDaymont Cleaning Algorithm:Daymont, C., et al., Automated identification of implausible values in growth data from pediatric electronic health records. J Am Med Inform Assoc, 2017. **24**(6): p. 1080-1087.

b Lowess method: Cohen, R.A. An introduction to PROC LOESS for local regression. in Proceedings of the twenty-fourth annual SAS users group international conference, Paper. 1999. Citeseer

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**Statistical modeling**

The mixed-effects model (which can be performed using ‘proc mixed’ in SAS or ‘lmerMod’ in R) for BMI included the following:

* Outcome: BMI expressed as a % of the 95th percentile (%BMIp95)
* Random intercepts and slopes representing time (coded as months before and after the initial PWMI visit) and an interaction term (treatment x time)
* Sex and age as covariates

The linear mixed effects model is written as:

Where:

months = BMI measurement was taken at this # of months before / after 1st PWMI visit

intv = 0: BMI measurement occurred before or during 1st PWMI visit, 1: BMI measurement occurred after 1st PWMI visit

months\*intv = interaction

The same equation was used to model BP expressed as BP mmHg. In addition, this equation was used to model %BMIp95 and BP for Referred and Eligible children, using the time point as defined in the Methods section of the manuscript.

**References**

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