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Two method measurement for adolescent obesity epidemiology: Reducing the bias in self report of height and weight

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Abstract

Background—Despite validation studies demonstrating substantial bias, epidemiologic studies typically use self-reported height and weight as primary measures of body mass index due to feasibility and resource limitations.

Purpose—To demonstrate a method for calculating accurate and precise estimates that use body mass index when objectively measuring height and weight in a full sample is not feasible.

Methods—As part of a longitudinal study of adolescent health, 1,840 adolescents (aged 12–18) self-reported their height and weight during telephone surveys. Height and weight was measured for 407 of these adolescents. Sex specific, age-adjusted obesity status was calculated from self-reported and from measured height and weight. Prevalence and predictors of obesity were estimated using 1) self-reported data, 2) measured data, and 3) multiple imputation (of measured data).

Results—Among adolescents with self-reported and measured data, the obesity prevalence was lower when using self-report compared to actual measurements ($p < 0.001$). The obesity prevalence from multiple imputation (20%) was much closer to estimates based solely on

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IMPLICATIONS AND CONTRIBUTION

BMI based on self-reported height and weight is typically underestimated by adolescents. The two-method measurement design offers a strategy for improving BMI estimates in studies primarily relying on self-reported height and weight data when resources for collecting measured data in a full cohort are unavailable.

measured data (20%) compared to estimates based solely on self-reported data (12%), indicating improved accuracy. In multivariate models, estimates of predictors of obesity were more accurate and approximately as precise (similar confidence intervals) as estimates based solely on self-reported data.

Conclusions—The two-method measurement design offers researchers a technique to reduce the bias typically inherent in self-reported height and weight without needing to collect measurements on the full sample. This technique enhances the ability to detect real, statistically significant differences, while minimizing the need for additional resources.

INTRODUCTION

Despite well-recognized limitations,[1–10] large epidemiologic studies of adolescent health commonly use body mass index (BMI) based on self-reported height and weight as a primary measure of body fat because of feasibility and resource limitations. Compared to objective measures, self-reported height and weight can underestimate obesity prevalence among adolescents by 1.6% to 11.1%.[1–4] In general, girls and overweight or obese adolescents self-report heights and weights that underestimate their weight status more than boys and normal weight adolescents.[1,3–9] Age[4,5,7,10] and race[3,6] have also been linked with bias in self-report, but the findings are not consistent.[1] Underestimation of the true prevalence could bias researchers' estimates of relationships between adolescents' risk of obesity and predictors of interest, such as diet or physical activity.

Objectively measured height and weight data is substantially more expensive to obtain compared to self-reported data, particularly in large studies covering expansive geographic areas. In some epidemiological studies that use BMI as a primary outcome, researchers purposefully measure height and weight in a subsample to check the accuracy of self-reported measures.[2–10] However, researchers encounter a difficult decision when comparisons reveal substantial inconsistencies between the two measures. Using BMI based solely on self-report is less accurate, but limiting analyses only to those with measured data would substantially reduce the sample size, resulting in wider confidence intervals (i.e., less precision).

With the availability of techniques for handling missing data, such as multiple imputation,[11] researchers have recommended a two-method measurement design, in which missing data are deliberately incorporated into the study design.[12, 13] In the two-method measurement design, a relatively inexpensive, less valid measure is collected from the wider group of participants, while a more costly but more valid measure is collected from a subsample.[12, 13] Data from the less expensive measure is then used to estimate missing information for the more expensive measure so that analyses can be conducted on the entire sample.

The objective of this study was to demonstrate the two-method measurement design for obesity epidemiology with two examples. Both adolescent self-reported and measured height and weight data were used to calculate single estimates of 1) the prevalence of overweight/obesity and obesity, and 2) sports team participation, screen time, and fruit/vegetable consumption as predictors of obesity status. These estimates, which use both real and imputed BMI from measured height and weight, were compared to results separately using only self-reported or only measured data.

METHODS

Study participants were enrolled in an ongoing cohort study of adolescent health for which adolescents were surveyed annually by telephone. Survey methods have been previously described in detail elsewhere.[14–16] Data for this analysis were obtained between February

2007 and December 2008. During this time, telephone surveys were successfully collected from 73.3% (N=1,840) of the eligible adolescents (N=2,510). Participants were in grades 7 through 11 and attended over 100 different schools in New Hampshire and Vermont. The Dartmouth Committee for the Protection of Human Subjects approved all aspects of this research.

Height was assessed in the telephone survey by asking: "How tall are you without shoes?" Weight was assessed by asking: "How much do you weigh?" Using items adapted from the Youth Risk Behavior Survey,[17] adolescents were also asked about their sports team participation ("In the past 12 months, on how many sports teams did you play? Include any teams run by your school, work, or community groups"); screen time (sum of "What was the total amount of time you spent in the past seven days… [watching TV, DVD's, or videos?], [playing videogames or using the computer for things other than homework?]"); and fruit/vegetable consumption (sum of "In the past 7 days, how many times did you eat or drink… [fruits, including fresh or canned?], [vegetables, including fresh, frozen, canned, and salad, but not including French fries?]").

In order to evaluate the accuracy of BMI based on self-reported height and weight, eight schools with the greatest number of study subjects enrolled were identified and recruited to participate in a validation study. Researchers attempted to collect objective height and weight measurements of all study subjects within these schools. Eight hundred fifty six parents were contacted, of whom 57.4% (N=491) were still enrolled in a study school and provided active parental consent for schools to obtain and share height and weight measurements of their child. Lists of consented adolescents were then provided to nurses at each school. In six schools, either the school nurse (N=5) or a member of the research team (N=1) collected the measurements specifically for this study. Heights were measured to the nearest 0.1 cm using portable Seca 214 stadiometers. Weights were measured to the nearest 0.1 kg using Seca 770 digital scales that were precalibrated by the research team. Nurses and study staff were trained to collect the anthropometric measurements in accordance with recommendations from the CDC Surveillance Data Quality and Expansion Project for obtaining reliable anthropometric measurements in a school setting.[18] Two schools had already collected height and weight measurements as part of a grade-wide physical exam and so in these schools, the school nurse recorded the measurements of study participants on a standardized reporting form. Although parental consent was obtained for 491 adolescents, 10 could not coordinate a time with the school nurse, and 2 declined to participate. The final sample of 479 adolescents represents 56.0% of the originally eligible adolescents. The time between self-reported data and school measurements did not influence the findings. Because 72 participants had not completed the telephone survey and were missing self-reported height and weight data, our final sample comprised 1912 adolescents (1433 with self-reported measures only; 407 with self-reported and objective measures; 72 with objective measures only).

Adolescents' ages at the time of their surveys and school measurements were calculated using their date of birth, the survey date, and the date of school measurement. Sex-specific BMI-for-age z-scores based on self-reported height and weight and measured height and weight were computed using the CDC SAS macro.[19] Z-score equivalents of sex-specific BMI-for-age percentile cutoffs were used to identify overweight/obese (BMI greater than or equal to the 85th percentile or z-score of 1.04) and obese (BMI greater than or equal to the 95th percentile or z-score of 1.65) adolescents.

Statistical Analyses

Three modes of analysis, using 1) self-reported BMI z-scores, 2) measured BMI z-scores, and 3) multiple imputation (of measured values) by chained equations[20] were used to compute three different estimates in two examples. In the first example, the prevalence of overweight/obesity and obesity were examined by sex, age, and race. In the second example, sports team participation, screen time, fruit and vegetable consumption, sex, age, and race were examined as predictors of obesity – this is a simplified version of the model described in Drake et al.[21] Poisson regression was used to determine risk ratios, with robust[22] cluster[23] variance estimates to account for the binomial outcome variable[24] and the within-school correlation. Standard errors, effective sample sizes, and confidence intervals were used to assess precision, such that more precise models have smaller standard errors, narrower confidence intervals, and larger effective sample sizes. Accuracy was approximated by comparing estimates from solely self-reported data and from multiple imputation to the estimates from solely measured data.

The imputation model for the first example included self-reported BMI z-scores, measured BMI z-scores, weight status variables, sex, age, race, and first order interactions of all variables. Sports team participation, screen time, and fruit/vegetable consumption were added to the imputation model in the second example. Measured BMI z-scores and corresponding weight status variables were missing for 74.9% of the sample; other study variables were missing for between 0.0% and 3.7% percent of the sample. Ordinary least squares and logistic regression models were used to predict continuous and binary outcomes, respectively. Because the intraclass correlation coefficient describing the percentage of between school variance in BMI z-scores was less than 0.0001, school-level clustering was not accounted for in the imputation model. In accordance with updated recommendations,[25] 60 imputed datasets were used because of the large percentage of adolescents without measured height and weight data. To simulate the effect of having obtained measurements from a smaller sample, the multiple imputation models were also estimated using only 50% of the measured BMI z-scores and corresponding weight status variables; these results were then compared to the original estimates that used all the measured data. All analyses were conducted in STATA version 11 (StataCorp LP, College Station, Texas).

RESULTS

As shown in Table 1, the sample was equally distributed by sex, and the majority was white. Compared to those with only self-reported BMI data, the subsample with measured BMI data contained a slightly higher percentage of older adolescents ($p<0.001$). Although there were more boys than girls with measured BMI data, this difference was not statistically significant ($p=0.17$). Based on self-report, the prevalence of overweight/obesity was slightly higher among adolescents with measured BMI data (31.2%) compared to adolescents with only self-reported data (26.7%). A similar pattern was seen for the prevalence of obesity based on self-report (14.7% vs. 11.4%, respectively). Among the 407 adolescents with both self-reported and measured BMI data, the prevalence of overweight/obesity based on measured BMI was 4.9% higher than BMI based on self-reported data (36.1% vs. 31.2%, respectively; $p<0.001$). The prevalence of obesity based on measured BMI was 6.2% higher than the prevalence based on self-reported BMI (20.9% vs. 14.7%, respectively; $p < 0.001$).

For the first example, Table 2 displays the prevalence of overweight/obesity and obesity, by sex, for three modes of analysis: using only self-reported height and weight data, using only measured height and weight data, and using multiple imputation. Prevalence estimates from multiple imputation (e.g. obesity prevalence = 20%) were much closer to estimates from measured data alone (20%) compared to estimates from self-reported data alone (12%). This was especially true for girls, whose estimates from multiple imputation (e.g. obesity = 18%) and from measured data alone (18%) were much were larger than their estimates from self-reported data alone (8%). Boys’ estimates, and the estimates of other demographic groups, were generally more similar across the three analytic models used to predict prevalence.

Compared to measured data, estimates from multiple imputation had smaller standard errors and a larger effective sample size (better precision). Compared to estimates based on self-reported data, estimates from multiple imputation had larger standard errors and a lower effective sample size (worse precision), but presumably less bias. The effective sample size calculation indicated that similar precision with multiple imputation estimates would be achieved if the number of adolescents with measured BMI was doubled, or the number of adolescents with self-reported data was approximately halved.

For the second example, Table 3 displays adjusted relative risks of obesity by sports team participation, screen time, fruit/vegetable consumption, sex, age, and race using only self-reported height and weight data, using only measured height and weight data, and using multiple imputation. This example demonstrates the utility of the two-method measurement for examining multivariate associations. Compared to the model using solely self-reported data, relative risks for all variables in the multiple imputation model were closer to relative risks in the model using solely measured data, indicating improved accuracy. For example, the relative risk of 0.78 for sports team participation based on self-reported BMI indicates that adolescents' risk of obesity decreases 22% for every additional sport they play. The model using multiple imputation indicates that adolescents' risk of obesity would decrease by 18%, providing a closer approximation to the model based on actual BMI measures, which indicated a 14% decreased risk of obesity. Confidence intervals in the multiple imputation model were narrower than confidence intervals in the model using only measured data and approximately the same as the confidence intervals in the model using only self-reported data.

In our simulation model, in which we dropped measured data for 240 adolescents (50% of the 479 adolescents for whom we obtained measured data), the overall prevalence estimates from multiple imputation (e.g. obesity=20%) were very similar to the estimates from multiple imputation with the full sample of measured data (20%). Sex-specific estimates (girls=18%; boys=21%) were also similar to the original estimates (girls=18%, boys=23%). As expected, these estimates were less precise; the overall effective sample size estimate dropped from 889 to 471. The relative risk estimates using only half the measured data for our second example were also similar to the estimates obtained with the full sample of measured data, and the confidence intervals were only slightly larger. For example, the relative risk for sports team participation in the simulation model was 0.80 (95% CI = 0.71, 0.90) compared to 0.82 (95% CI = 0.74, 0.91) in the full imputation model.

DISCUSSION

The two-method measurement design offers researchers a technique with similar benefits of objectively measured height and weight data, while averting the need to measure height and weight in the full sample. Adolescents, especially girls and those with self-reported BMIs at the upper extreme of the distribution, tend to underestimate their weight status,[1] which could bias parameter estimates in epidemiological studies. By measuring height and weight in a subsample, and obtaining self-reported height and weight in the full sample, researchers can use multiple imputation techniques to estimate accurate estimates in the full sample.

In this study, the obesity rate was 8% lower when based on self-reported compared to measured height and weight. Consistent with previous research,[1, 3–9] this difference was larger for girls (10% lower) than it was for boys (5% lower). However, despite having measured height and weight data for only 25% of our sample, our multiple imputation estimate of the obesity prevalence in the full sample was approximately the same as the estimate from the subsample with measured data. For these prevalence estimates, standard errors from self-reported data were slightly lower than estimates from multiple imputation, implying a tradeoff between accuracy and precision.

In the multivariate models predicting obesity, results indicated that risk factor estimates from the multiple imputation model were more accurate than and approximately as precise as estimates from solely self-reported data. The similarity of estimates from multiple imputation to estimates from measured data indicated improved accuracy. The similarity of the confidence intervals around regression coefficients for sports team participation, fruit and vegetable consumption, and screen time indicated similar precision. Consequently, the estimates from multiple imputation had an improved ability to detect real statistically significant relationships compared to estimates using only self-reported data. Interestingly, some predictors of obesity (screen time and sex) were statistically significant when using self-reported BMI data, but not when using measured data or multiple imputation of measured data. This suggests that girls and adolescents who reported less screen time may under-report their weight compared to boys and adolescents who reported more screen time.

For the multivariate models using only self-reported or only measured data, the sample sizes are lower compared to the corresponding prevalence estimates in Table 2 because observations with any missing data are dropped. This strategy is called case deletion, and is the default in most statistics packages. It can seriously deteriorate the sample size in models with numerous covariates and should be avoided by using multiple imputation or other missing data techniques.

Many researchers remain skeptical of imputing data because its mathematical foundation and application are not widely taught. However, multiple imputation is an accepted, straight-forward procedure and the computer algorithms for its implementation have recently become available in most major statistical packages (e.g. STATA), and are extremely user-friendly. Although multiple imputation has proven robust in numerous applications, this study demonstrates its value for addressing a common problem in epidemiological studies of obesity.

The relaxed use of a large number of predictor variables and interactions in the imputation models might surprise readers who are unfamiliar with missing data techniques. The goal of imputation is to predict, as accurately as possible, values for the missing data.[26] Because interpretability and explanatory sparseness are not a priority, models should include all variables that might explain some variance, as well as all interactions that might capture nuanced relationships between the variables. Simulation studies support this axiom of multiple imputation, and have found that overly inclusive models are greatly preferred to models that make minimal use of auxiliary variables.[27]

For many large epidemiological studies, acquiring measured height and weight data for even 25% of the full sample would be prohibitively expensive. We found that our multiple imputation estimates would have been similar if we had only collected half of the measured height and weight data that we actually collected (i.e. 12.5% [n=239] versus 25% [N=479] of the total sample). Needing to collect measured data for fewer participants may allow researchers to afford a completely random sampling strategy, which would have been preferable to our method. Additionally, quota sampling is a useful strategy for obtaining sufficient data of all demographic groups in a small subsample.

One limitation of this study was the use of a non-random subsample of adolescents for whom measured height and weight data were obtained. To maximize efficiency and minimize costs, measurements were obtained for adolescents in the eight schools containing the most participating students. Systematic differences in how adolescents within these schools misreported their height in weight could have biased our results. However, we considered this unlikely because school-level factors explained approximately zero variance in BMI (based on the intraclass correlation coefficient), and because there were few covariate differences between adolescents with and without measured heights and weights. Still, investigators need to carefully consider how selection bias might influence results when there is non-random sampling, and from an analysis standpoint, a completely random sampling strategy is always preferable. Also, actual measurements were obtained for only 56% of the adolescents that the researchers originally attempted to contact for this purpose. In this study, BMI estimates based on measured data differed from BMI estimates based on self-reported data for two reasons. First, adolescents generally underreported their weight status. Second, adolescents who had measured data were slightly more likely to be overweight or obese compared to the kids for whom only self-reported data were available. These were not considered major limitations, because multiple imputation estimates reflected both of these differences. An underlying assumption of multiple imputation is that missingness depends only on variables included in the model and on their relationships being correctly specified.[11] Thus, if girls or overweight adolescents were less likely to agree to have their height and weight measured than boys or normal weight adolescents, the assumption would be safely met. However, if bias in self-report of height and weight differed by variables not included in the model, such as self-esteem, the multiple imputation estimates could be biased. This was considered unlikely here because self-reported BMI z-scores and demographic variables predicted obesity status with excellent accuracy (94.5%). Because younger adolescents were underrepresented in the subsample with measured data, our model may not have worked as well for the 12–13 year old adolescents in our sample. In addition, self-reported and measured height and weight were not obtained concurrently. The possibility that the accuracy of self-reported height and weight could increase if adolescents had been measured closer to the same date was considered. However, these data did not demonstrate this temporal relation, and inclusion of a time between measurements effect in the models did not alter the results.

BMI based on self-reported height and weight is typically underestimated by adolescents, especially by girls and overweight or obese adolescents. This study extended previous research of reporting bias by using available objective measurements and multiple imputation to generate more accurate weight status estimates in the full sample. The two-method measurement design offers a strategy for improving BMI estimates in studies primarily relying on self-reported height and weight data. This method is particularly useful when resources for collecting measured height and weight data in a full cohort are unavailable.

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Abbreviations

BMI	Body Mass Index
CDC	Centers for Disease Control and Prevention
SD	Standard Deviation
CI	Confidence Interval
SE	Standard Error

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Table 1

Frequency of demographics by availability of BMI data (Column %)

	Only Self-Reported BMI Available (N=1433)	Both Self-Reported and Measured BMI available (N=407)	Only Measured BMI available (N=72)
Gender			
Girl	719 (50.2)	191 (46.9)	32 (44.4)
Boy	714 (49.8)	216 (53.1)	40 (55.6)
Age			
12–13	278 (19.4)	63 (15.5)	18 (25.0)
14	543 (37.9)	110 (27.0)	18 (25.0)
15	446 (31.1)	126 (31.0)	26 (36.1)
16–18	166 (11.6)	108 (26.5)	10 (13.9)
Race			
Not White	95 (6.7)	25 (6.1)	15 (20.8)
White	1331 (93.3)	382 (93.9)	57 (79.2)
Based on Self-Report			
Overweight/Obese (≥85%)			
No	1050 (73.3)	280 (68.8)	
Yes	383 (26.7)	127 (31.2)	
Obese (≥95%)			
No	1269 (88.6)	347 (85.3)	
Yes	164 (11.4)	60 (14.7)	
Based on Measurements			
Overweight/Obese (≥85%)			
No		260 (63.9)	50 (69.4)
Yes		147 (36.1)	22 (30.6)
Obese (≥95%)			
No		322 (79.1)	61 (84.7)
Yes		85 (20.9)	11 (15.3)
Sports Team Participation in past 12 months			
0	360 (25.1)	123 (30.2)	6 (37.5)
1–2	514 (35.9)	142 (34.9)	7 (43.7)
> 2	559 (39.0)	142 (34.9)	3 (18.8)
Screen Time in past week (hours)			
< 6	495 (34.6)	111 (27.3)	6 (40.0)
6–11	483 (33.7)	147 (36.1)	4 (26.7)
> 11	454 (31.7)	149 (36.6)	5 (33.3)
Times fruits and vegetables were consumed in past week			
< 6	463 (32.4)	161 (39.6)	4 (25.0)
6–9	436 (30.5)	150 (36.9)	6 (37.5)
> 9	532 (37.2)	96 (23.6)	6 (37.5)

Table 2

Estimates of body mass from self-report, objective measurements, and multiple imputation

		Self-Reported BMI Data (n=1840)		Measured BMI Data (n=479)		Multiple imputation (n=1912)	
		Prevalence (SE)	n	Prevalence (SE)	n	Prevalence (SE)	n[a]
	Total	0.28 (0.01)	1840	0.35 (0.02)	479	0.34 (0.02)	913
Overweight/ Obesity (≥85%)	Girls	0.23 (0.01)	910	0.36 (0.03)	223	0.33 (0.02)	471
	Boys	0.32 (0.02)	930	0.35 (0.03)	256	0.34 (0.02)	454
	Total	0.12 (0.01)	1840	0.20 (0.02)	479	0.20 (0.01)	889
Obesity (≥95%)	Girls	0.08 (0.01)	910	0.18 (0.03)	223	0.18 (0.02)	449
	Boys	0.16 (0.01)	930	0.21 (0.03)	256	0.23 (0.02)	412

[a]effective n indicates the sample size of measured BMI data needed to obtain standard errors of the same size as the multiple imputation model

SE = standard error

Table 3

Adjusted relative risk of obesity from self-report, measurements, and multiple imputation

	Relative Risk (95% Confidence Interval)		
	Self-reported BMI data (n=1830)	**Measured BMI data (n=422)**	**Multiple imputation (n=1912)**
Sports Team Participation in past 12 months	0.78 (0.71, 0.87)	0.86 (0.72, 1.03)	0.82 (0.74, 0.91)
Screen time in past week (hours)			
< 6	Reference	Reference	Reference
6–11	1.35 (0.98,1.87)	0.74 (0.43,1.29)	1.11 (0.81,1.53)
> 11	1.63 (1.21,2.20)	0.96 (0.66,1.39)	1.18 (0.90,1.56)
Times fruits and vegetables were consumed in past week			
< 6	Reference	Reference	Reference
6–9	0.80 (0.57,1.11)	1.03 (0.49,2.15)	0.87 (0.63,1.19)
> 9	0.73 (0.53,1.02)	0.84 0.44,1.61	0.77 (0.56,1.05)
Gender (boy)	1.72 (1.34,2.20)	1.16 (0.99,1.35)	1.19 (0.94,1.53)
Age	1.00 (0.91,1.11)	0.88 (0.76,1.02)	0.99 0.89,0.1.09)
Race (white)	0.86 (0.54,1.36)	0.46 (0.31,0.67)	0.80 (0.51,1.25)