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Distance and Percent Distance from Median BMI as Alternatives to BMI z-score

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Abstract

Body mass index z-score (BMIz) based on the CDC growth charts is widely used, but it is inaccurate above the 97[th] percentile. We explored the performance of alternative metrics based on the absolute distance or % distance of a child's BMI from the median BMI for sex and age.

We used longitudinal data from 5628 children who were first examined < 12 y to compare the tracking of three BMI metrics: distance from median, % distance from median, and % distance from median on a log scale. We also explored the effects of adjusting these metrics for age differences in the distribution of BMI. The intra-class correlation coefficient (ICC) was used to compare tracking of the metrics.

Metrics based on % distance (whether on the original or log scale) yielded higher ICCs than those for distance from median. The ICCs of the age-adjusted metrics were higher than for the unadjusted metrics, particularly among children who were either (1) overweight or had obesity, (2) younger, and (3) followed for > 3 years. The ICCs of the age-adjusted metrics were also higher than those for BMIz among children who were overweight or obese.

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Dr. Freedman conceptualized and performed the analysis, drafted the initial manuscript, and revised the manuscript.
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Unlike BMIz, these alternative metrics do not have an upper limit and can be used for assessing BMI in all children, even those with very high BMIs. The age-adjusted % from median (on a log or linear scale) works well for all ages, while unadjusted % from median is better limited to older children or short follow-up periods.

Keywords

BMI; children; metrics; obesity

Introduction

The 2000 Centers for Disease Control and Prevention (CDC) growth charts [1,2] are widely used to standardize body mass index (BMI) for differences by sex and age. The charts consist of ten BMI percentiles from the 3rd to the 97th, estimated using various smoothing methods [1,3]. Overweight is classified as BMI ≥ 85th percentile for a child's sex and age, while obesity is a BMI ≥ 95th percentile of these growth charts [4].

These percentiles were subsequently used to derive the three age-specific parameters needed for the LMS method [3,5,6]: L (power transformation for normality), M (median), and S (generalized coefficient of variation). This allows one to calculate the sex-specific BMI-for-age z-score (BMIz) and corresponding percentile for any child. BMI z-score has been widely used in cross-sectional and longitudinal analyses where BMI is treated as a continuous variable, including those evaluating the efficacy of interventions among children with very high BMI. Continuous variables are best analyzed as continuous rather than dichotomized [7,8], but there are several limitations of the BMI z-score based on the CDC growth charts.

Because the BMI distribution in childhood in the United States is very skewed, transforming it to BMIz shrinks the scale at the upper end. The degree of skewness shows itself in the L parameter, the BMI power transformation, being far smaller than 1 (where 1 indicates no transformation) and between −2 and −3 at most ages. These low values of the L parameter lead to the upper tail of the BMI distribution being compressed into a narrow z-score range at most ages [9,10] and an upper limit for BMIz that varies substantially by age and sex [11]. This compression can result in similarly aged children with markedly different BMIs having similar z-scores. Further, because the maximum value of BMIz in the CDC growth charts differs by sex and age, it is possible for (say) for the BMI of a 2-year-old girl to increase substantially over the next two years, but for her BMIz to decrease by more than 1 SD [12]. Similar limitations have also been noted for BMIz based on other growth charts constructed using the LMS method [11,13]. A further problem with the CDC charts is that high z-scores do not correspond well with the observed data [14] as they were estimated from data between the 3rd and 97th percentiles.

These limitations have resulted in various alternatives being proposed for analyses with BMI as a continuous variable. They include focusing on changes in BMI rather than in BMIz in longitudinal analyses [15,16], expressing a child's BMI as a percentage of the 95th percentile (%BMIp95) [9,10,14,17] and using a modified z-score that extrapolates a fixed standard deviation outwards [18]. Although these metrics avoid the compression of very high BMIs into a narrow range of z-scores, it is unclear if they are useful for lower BMIs and if they convey similar information across ages. Furthermore, they are tied to the CDC growth charts at only one point (the 95th percentile for %BMIp95) or two points (the median and a z-score of ± 2 for the modified z-score [19]).

It is possible, however, to create other BMI metrics that are more strongly linked to the CDC growth charts and which, unlike %BMIp95, use the more robust estimate of the median. In the LMS transformation, for example, L can be set to a fixed value less extreme than −2 or −3, such as 1 (corresponding to no transformation), 0 (log transformation) or another constant, while retaining the M and S parameters. This leads to a modified metric that can be interpreted as either absolute distance (kg/m^2) or % distance from the median, avoiding the compression of very high BMIs into a narrow z-score range. Further, knowing a child's distance or % distance from the median may be more interpretable than knowing their modified z-score or %BMIp95. Expressing BMI as a % distance from the median is similar to expressing a child's weight as a percentage of the median (standard) weight, a metric that predates the use of z-scores and centiles [20,21].

Our objective is to evaluate the performance of three alternative metrics to BMIz based on setting L equal to 1 or 0. These two L values result in metrics that are interpretable as the distance of BMI from the median in absolute (kg/m^2) and proportional (%) terms, with the latter calculated on both linear and log scales. Thus, the three metrics are: (1) absolute distance from the median, (2) % distance from the median, and (3) % distance from the median on a log scale. We show how these metrics are related to the LMS transformation, and then examine the tracking of these metrics over time and the effects of age adjustment. Because of the well documented poor tracking of BMIz among children with severe obesity [12,22], we do not emphasize comparisons with this metric. The new metrics can be used in conjunction with the current cut-points for overweight (BMI between the 85th and 94th percentiles of the CDC growth charts) and obesity (BMI ≥ 95th percentile).

Subjects and Methods

Study Sample

The Bogalusa Heart Study examined the development of risk factors for cardiovascular disease [23]. Seven cross-sectional studies of school-children were conducted from 1973–1974 through 1992–1994, with each examining about 3500 children. Pre-school schoolchildren (n=714) were also examined in 1973–74. We also used information from 640 18- and 19-year-olds who were examined in various studies during this period [24]. All procedures were approved by ethics committees at Louisiana State University Medical Center and Tulane School of Public Health. Parental permission and assent of the child were obtained prior to participation, and informed consent was obtained for participation as an adult. The current study is a secondary analysis of these data.

Altogether these studies involved 27,212 examinations among 11,665 2- to 17-year-olds. As previously described [25], we excluded data thought to be biologically implausible [26] or inconsistent across examinations. To focus on tracking through childhood, we restricted the analysis to children who were examined twice or more, with the first visit occurring before age 12 y. This was because the value of S (coefficient of variation) varies substantially with age before age 12 y but is relatively constant among older children [10,27], and if S is constant, age adjustment will not influence % distance on either the linear or log scale. These exclusions resulted in a sample of 5628 children with 18,381 measurements, mean 6.8 years from first to last measurement.

BMI Metrics

Height was measured to the nearest 0.1 cm and weight to the nearest 0.1 kg; BMI was calculated as kg/m^2. BMI-for-age z-score (BMIz) was calculated using the sex-age-specific values of L (power transformation to achieve normality), M (median), and S (coefficient of variation) [5,6] in the CDC growth charts [1,26]

$$\mathrm{BMIz} = \frac{(\mathrm{BMI/M})^{\mathrm{L}} - 1}{\mathrm{L} \times \mathrm{S}}. \tag{1}$$

If the value of L is set to 1 or 0, the LMS transformation can be interpreted as either the distance (kg/m^2) or % distance from the median (on a linear or logarithmic scale). When L = 1 (i.e. untransformed BMI) equation (1) can be multiplied by M / M to yield

$$BMIz_1 = \frac{\mathrm{BMI} - \mathrm{M}}{\mathrm{M} \times \mathrm{S}}. \tag{2}$$

Multiplication of both the numerator and denominator of (2) by 100 / M yields

$$BMIz_1 = \frac{(100 \times \mathrm{BMI/M}) - 100}{100 \times \mathrm{S}} \tag{3}$$

where the subscript 1 in BMIz$_1$ indicates L = 1. Similarly, when L = 0 (corresponding to log BMI) equation (1) can be written as

$$BMIz_0 = \frac{100 \times \log(\mathrm{BMI/M})}{100 \times \mathrm{S}}. \tag{4}$$

Formulas 2 through 4 are alternative z-scores; note that $M \times S$ in (2) corresponds to the age-specific standard deviation. If (2) is multiplied by M × S, BMI is expressed as absolute distance (kg/m^2) from the median. Similarly if (3) and (4) are multiplied by 100 × S, they express BMI as the % distance from the median; equation (4) expresses it on a logarithmic scale resulting in symmetrical and equal percentages [28]. To illustrate equation (3) vs. (4), consider two girls, one whose BMI is twice the median and the other whose BMI is half the median. Using (3) their distances from the median are +100% and −50%, while with (4) their distances are +69% and −69%.

Thus (2) to (4) measure the distance from the median as respectively

$$(\mathrm{BMI} - \mathrm{M})\ \mathrm{kg/m}^2 \tag{5}$$

$$[(100 \times \text{BMI/M}) - 100]\,\% \tag{6}$$

and

$$100 \times \log(\text{BMI/M})\,\%. \tag{7}$$

It follows that (2) to (4), as forms of z-score, are measures of BMI distance from the median scaled by M and/or S. But M and S vary by age, so the relevance of the distance also varies by age. To address this, (2) to (4) can be multiplied by values of M and/or S for some reference age, say M_{ref} and S_{ref}, which is equivalent to scaling (5) to (7) as follows:

$$(\text{BMI} - \text{M}) \times \frac{M_{ref} \times S_{ref}}{M \times S} \tag{8}$$

$$[(100 \times \text{BMI/M}) - 100] \times \frac{S_{ref}}{S} \tag{9}$$

and

$$100 \times \log(\text{BMI/M}) \times \frac{S_{ref}}{S}. \tag{10}$$

In this analysis we use a reference age of 20 y, but if desired, a different reference age could be used for values of M_{ref} and S_{ref}. Note that (8) to (10) are equivalent to (2) to (4) multiplied by either $M_{ref} \times S_{ref}$ or S_{ref}, so not only are they age-adjusted metrics, they are also scaled z-scores.

To illustrate the metrics, we consider three girls of different ages whose BMI is 140% of the 95th percentile [14,17] (Table 1). For the 3-year-old, her BMI of 25.6 is a distance of 9.9 kg/m^2 above her age-sex-specific median. Adjusted to age 20 y, her distance is $9.9 \times \frac{(21.7 \times 0.153)}{(15.7 \times 0.079)} = 26.5$ kg/m^2 from the age-20 median, from (8). This adjustment scales the +9.9 kg/m^2 distance to the comparable distance at reference age 20 when the BMI distribution is more variable. Similarly, from (6) and (9), her BMI as % distance from the median is $(100 \times 25.6/15.7) - 100 = 63\%$ unadjusted, or $63\% \times 0.153/0.079 = 122\%$ adjusted. Finally, her % distance from the median on the log scale, from (7) and (10), is $100 \times log(25.6/15.7) = 49\%$ unadjusted, and $49\% \times 0.153/0.079 = 95\%$ adjusted. In general, for high BMI a child's % distance, whether unadjusted or adjusted, is about 20% to 30% lower when calculated on the log vs. linear scale.

Figure 1 focuses on three girls whose BMI tracks at 60%, 110% and 160% distance from the median. Figure 1A compares unadjusted (dashed lines) and adjusted (solid lines) % from the median, while Figure 1B shows BMIz. On the BMI scale (A) the unadjusted curves are fairly equally spaced at all ages, while the adjusted curves, which account for differences in the dispersion of BMI by age, are closer together at younger ages. At age 2 y for example, BMI on the top 160% curve is about 30 adjusted but much higher at 43 unadjusted. On the BMIz scale (B) the upper two curves are much closer together than the lower two, and this effect becomes more marked with increasing BMIz. The three dots in the left panel represent the examples in Table 1, BMIs that are 140% of the 95th percentile at ages 3, 10, and 18, and they are all close to 110% adjusted distance. However, the corresponding unadjusted % distances vary substantially (63% to 100%, Table 1) showing the difficulty in comparing unadjusted % distance across a wide age range.

Statistical Methods

The unadjusted and age-adjusted versions of the three BMI metrics are called: distance from the median (5) and (8), % from the median (6) and (9), and log % from the median (7) and (10). The metrics are compared on the basis of how well they tracked over time within individuals, using the intraclass correlation coefficient (ICC) as a measure of repeatability [29,30]. One property of a good BMI metric is that it should not change materially with age, so that values can be compared between younger and older children.

In contrast to the Pearson correlation, the ICC focusses on within-child clustering, contrasting the between-child and within-child variances. For example, if two girls had BMIs of 20 and 25 initially, and both BMIs increased by 4 kg/m^2 upon reexamination, the Pearson correlation would be 1. The ICC, however, accounts for the 4 kg/m^2 difference between examinations, and can be estimated from a one-way analysis of variance using the mean square between children, 2 × variance $\left(\frac{20+24}{2}, \frac{25+29}{2}\right) = 25$, and mean square (error) within children, $0.5 \times \left(4 \times 2^2\right) = 8$; the ICC would be $\frac{25 - 8}{25 + 8} = 0.52$. A higher ICC (maximum 1.0) indicates greater tracking (repeatability) over time.

ICCs for each metric were examined in the overall sample, and also stratified by BMI status, age at initial examination, and mean time interval between the first and last examinations. All analyses were performed in R [31], and the ICCs were calculated from the variance components of mixed-effects models using the lme4 package [32]. This corresponds to a one-way random effects ICC [29,30]. As this is a secondary analysis of a large dataset, power calculations were not performed.

Results

Table 2 shows descriptive characteristics at the first and last examinations, with mean ages 7.3 and 13.4 y. Mean BMI increased by 4.1 kg/m^2 between the examinations, and BMIz and the alternative BMI metrics also increased over time, indicating that, on average, children gained BMI faster than indicated by median BMI in the CDC growth charts.

Table 3 compares the ICCs for BMIz and the three BMI distance metrics using data from all 18,381 examinations (mean, 3.3 per child). Overall, the ICCs for the age-adjusted metrics and BMIz were very similar (0.83 to 0.84), while those for the unadjusted metrics were slightly lower (0.76 to 0.80). In contrast the ICC for BMI was only 0.52 (not shown), indicating the need to adjust BMI for age. Among the 935 children whose initial BMI was at or above the 85th percentile, the ICCs for the adjusted metrics (0.70 to 0.71) were larger than those for BMIz (0.62) and the unadjusted metrics (0.54 to 0.60), with the lowest ICC seen for distance from the median. The ICCs of the adjusted metrics were also substantially higher than those for BMIz and the unadjusted metrics in the subsets of children with higher values of their initial BMI (above the 95^{th}, 97^{th} or 99^{th} percentiles). Among the 87 children who had an initial BMI ≥ 99^{th} percentile, the ICC for adjusted log % distance from the median was lower (0.44) than were the ICCs for the other adjusted metrics (0.52).

Figure 2 shows that the ICCs rose with age at first examination, with the adjusted metrics performing better than the unadjusted, particularly in the youngest children. Beyond age 9 y the unadjusted and adjusted metrics, particularly for % distance, performed similarly. Of the unadjusted metrics, absolute distance from the median performed worst, while the three adjusted metrics performed similarly at all ages.

Figure 3 shows the ICCs falling with increasing time interval between the first and last examinations, indicating lower tracking as the length of follow-up increased. For intervals < 3 years (mean 2.5 years) there was little difference in the ICCs of the six metrics. For longer intervals, the ICCs fell more steeply for the unadjusted metrics, particularly distance from the median, while the ICCs for the adjusted metrics were similar.

Analyses of the ICCs stratified both by time interval and age at first examination (not shown) confirmed that there was little difference in the ICCs of the six metrics at any age among children re-examined within 3 years. Over longer time intervals, the ICCs of the adjusted metrics were larger than those of the unadjusted metrics for children first examined before 9 y of age.

Discussion

Despite the limitations of BMI z-score based on the LMS parameters of the CDC growth charts for children with severe obesity [10,11,14,15,33], it continues to be widely used for children with very high BMI [34–38]. As an alternative, we explored metrics that express a child's BMI as the absolute or percentage distance from their median BMI for age and sex. These metrics use the M (median) and S (coefficient of variation) parameters of the CDC growth charts and can be adjusted for age.

A desirable property of a BMI metric is that it should track over time so that changes can be identified. We assessed this tracking using the ICC, a statistic that contrasts between-child and within-child variability. Because these alternative metrics, unlike BMIz, do not compress very high BMIs into a narrow range that varies by sex and age, it is likely that they will more accurately characterize the BMIs of children in both epidemiologic and clinical research. These metrics may be particularly useful when assessing the BMI and longitudinal changes in BMI of children with a BMI ≥ 97^{th} percentile.

We found that when adjusted for age, the three BMI metrics performed similarly to BMIz among all children, unsurprisingly given that they are derived from the LMS transformation. However, among children who were either (1) overweight or had obesity, (2) younger, and (3) followed for > 3 years, the ICCs of the adjusted metrics were appreciably higher than those for the unadjusted metrics. Of note, the effects of initial age and length of follow-up were largely independent. Of the unadjusted metrics, the ICCs for % distance from median and log % distance from median were larger than those for distance from median, particularly at younger ages and over longer time intervals. There was little difference between the age-adjusted linear and log forms of % from the median in most analyses, among the 87 children who had an initial BMI ≥ 99th percentile, the ICC for the linear % distance was larger than for the log % distance (0.52 vs. 0.44)

These results are related to the parameters underlying the CDC growth charts. The M and S values of these parameters in these charts are very different before and after age 12 y [10,27], with M rising almost linearly after age 6 y and S increasing steeply between ages 5 and 12 y and then stabilizing. The higher ICCs for unadjusted % distance compared to absolute distance reflects the coefficient of variation S being less age-dependent than the standard deviation $M \times S$.

The lower ICC for BMIz among children with a high BMI reflects its compression at the upper end [3,9,11,14,16]. Further, the effect of age adjustment is larger among overweight and obese children because a) the metrics reflect distance from the median, b) this distance is greater for children with a high BMI, and c) the effect of age adjustment is to scale the distance by M and/or S, both of which are greater at age 20 than at younger ages. It could be argued that a BMI metric should be selected based on the magnitude of its associations with risk factors [39,40], but this may be difficult because cross-sectional correlations with risk factor levels are low (r ~ 0.2 to 0.4) [41,42] and the variability of these characteristics is strongly age-dependent.

The BMI metrics assessed in the current study could be used in conjunction with the current cut points for overweight (85th to 94 percentiles) and obesity (BMI ≥ 95th percentile) in the CDC growth charts. Although the adjusted BMI metrics correspond more closely to the BMI centiles in the growth charts than do the unadjusted metrics, it should be realized that there are substantial differences by sex and age. For example, the mean (range) adjusted % distance corresponding to the 95th centile is +33% (26 to 37) among boys and +40% (29 to 46) among girls. Levels of the adjusted metrics also differ substantially by race/ethnicity.

A reviewer suggests that accounting for kurtosis in the BMI distribution might alleviate the skewness problem and the resulting compression of very high BMIs into a narrow z-score range. For example, the WHO child growth standards explored modeling kurtosis in the BMI distribution by fitting the Box-Cox power exponential distribution [43]. However, attempts to model the BMI distribution in the CDC growth charts using the Box-Cox power exponential or Box-Cox t distribution [44] resulted in many values of the L (skewness) parameter being more negative than those in the current CDC growth charts. Therefore, adjusting for kurtosis does not alleviate the problem of extreme skewness in the CDC growth charts and the resulting compression of very high BMIs into a narrow range.

Several limitations of our results should be considered. Because the prevalence of obesity (BMI ≥ 95th percentile) is much lower in these analyses (9%) than currently in the United States (18.5%) [45], it is possible that we have underestimated the importance of age adjustment among contemporary children. Further, methods other than the ICC could be used to evaluate tracking, such as examining the ability of a high BMI to predict a high BMI in later life. It should also be noted that although we did not assess the other alternative BMI metrics that have been proposed, i.e., modified z-score [18,19] and %BMIp95 [10,14,17,46], these two metrics were highly correlated (r > 0.95) with adjusted % distance from the median. However, values of % distance from the median are more closely tied to the CDC growth charts and may be more interpretable than modified BMIz, or %BMIp95. As levels of these alternative BMI metrics likely vary by race/ethnicity, it would also be possible to examine these metrics within various subgroups.

Conclusions

Although BMIz continues to be widely used among children with very high BMI, it has serious limitations when BMI exceeds the 97th percentile. Of the alternatives we examined, % distance from median is better than absolute distance from median based on their ICCs. Although log % distance from median partially accounts for the skewness of the BMI distribution, we found some evidence to suggest that adjusted % distance from the median on the linear scale may superior. These alternative BMI metrics could supplement the current cut points in the CDC growth charts and would provide a more nuanced assessment for BMI over the 99th percentile to a wider audience (including families of children who have a very high BMI.) These alternative metrics would also be useful in long-term studies that assess the effects of obesity interventions among children with very high BMIs. For clinical purposes, it would also be possible to generate charts illustrating these metrics for children with BMI over the 97th percentile.

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Abbreviations:

BMI	body mass index
CDC	Centers for Disease Control and Prevention
%BMIp95	BMI expressed as a percentage of the 95th percentile
BMIz	BMI-for-age z-score
L	power transformation for normality
M	median

S	coefficient of variation

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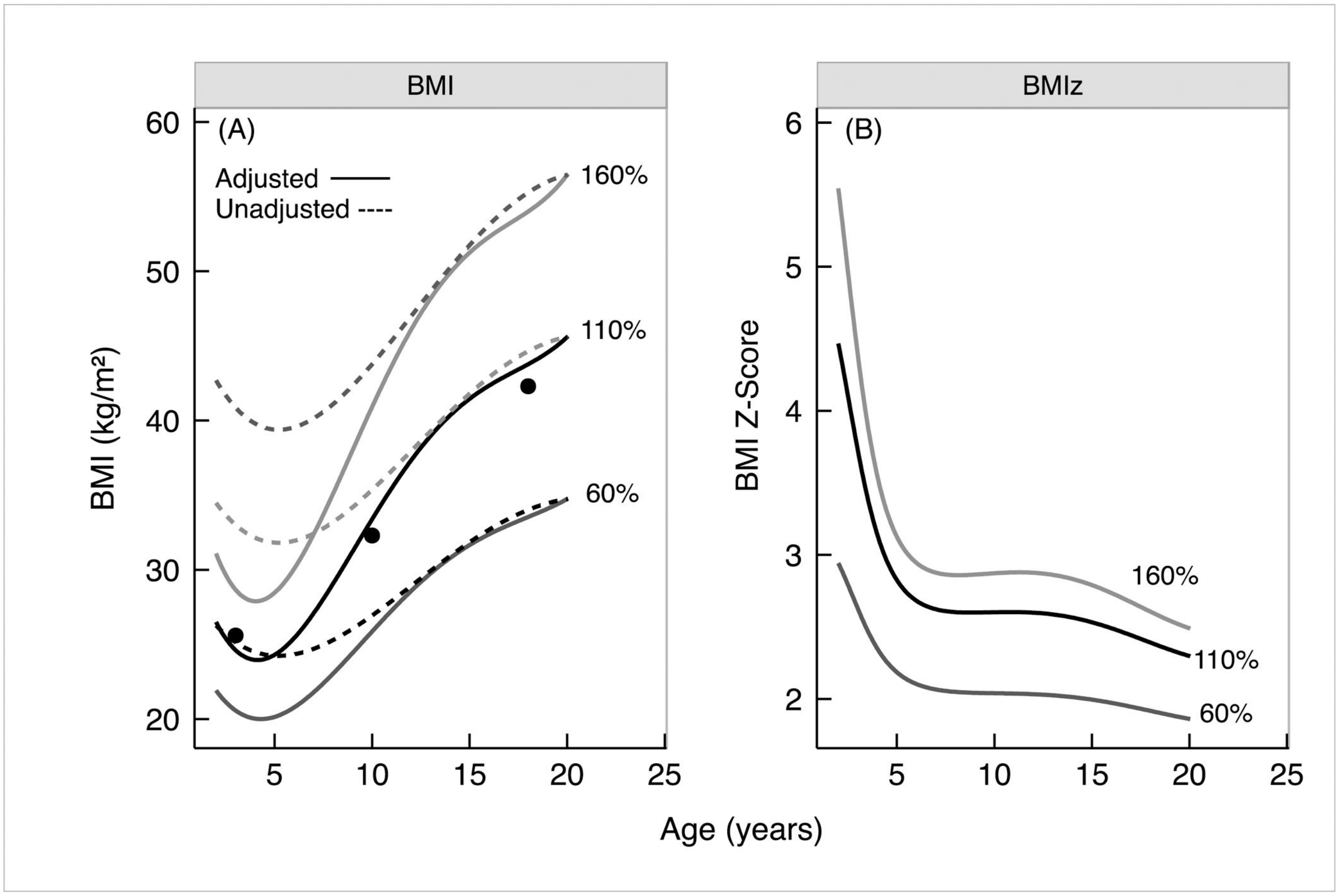

Figure 1.

BMI (A) and BMI z-score (B) by age for girls who have adjusted BMI distances (solid lines) from the median of 60%, 110% and 160%. These values correspond to BMIs of approximately 35, 45, and 55 kg/m^2 at age 20 years. The dashed lines in (A) represent the corresponding unadjusted % distance. The three points in the left panel represent the BMIs of a girl at age 3, 10, and 18 years who has a BMI that is 140% of the 95th percentile.

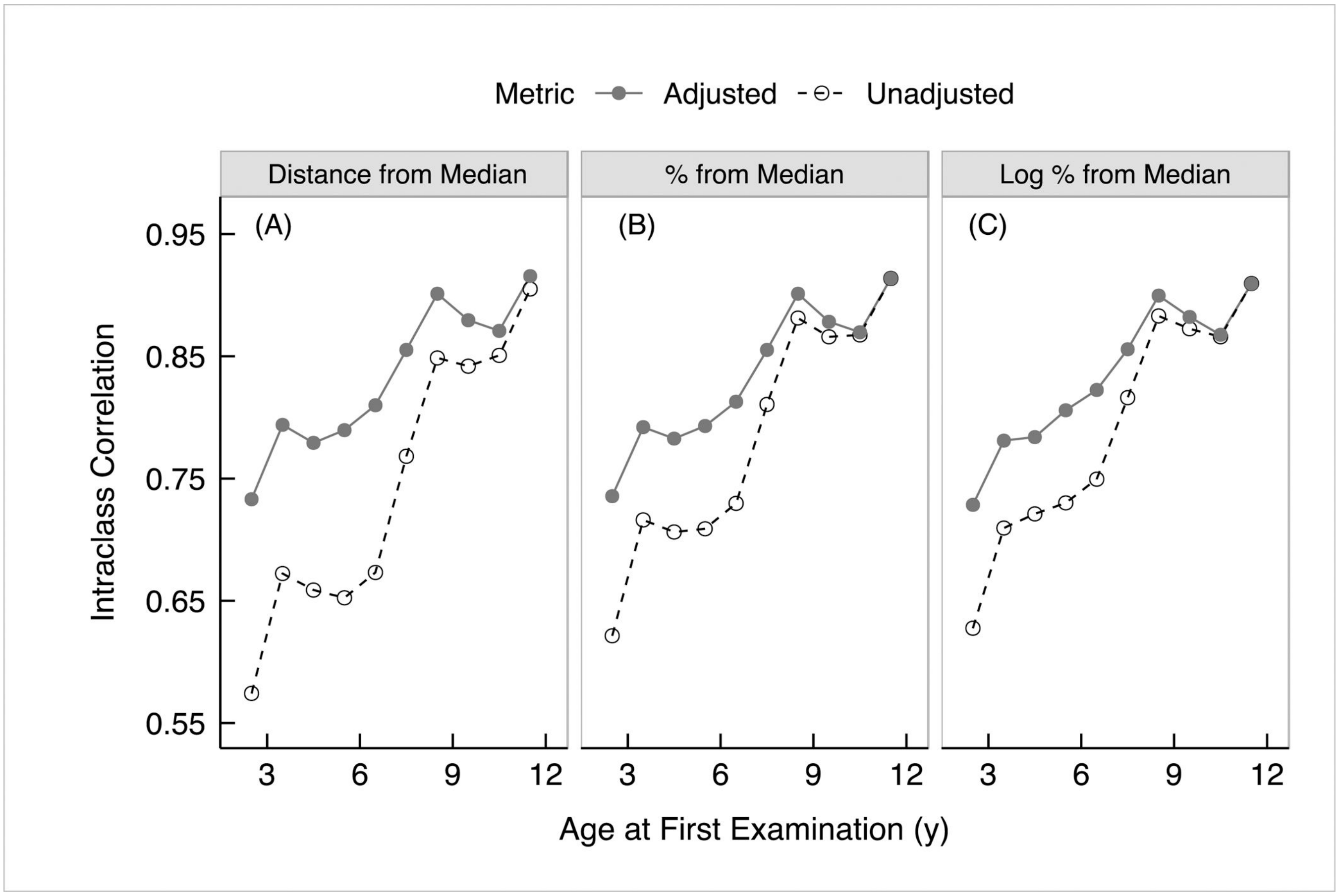

Figure 2.
Intraclass correlation coefficients for unadjusted and age-adjusted BMI metrics by age at first examination. The points represent the mean age at first examination in each group.

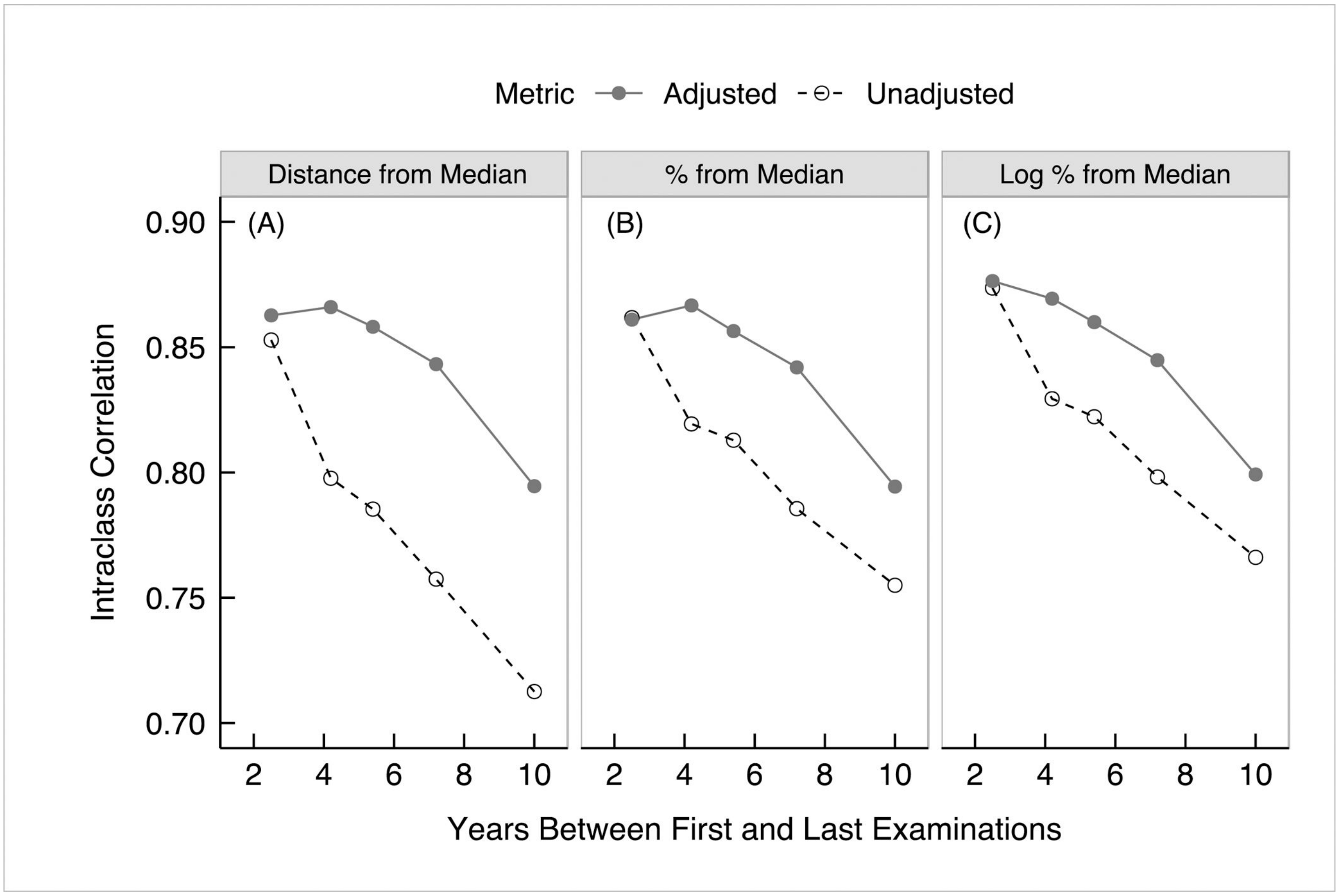

Figure 3.
Intraclass correlation coefficients for unadjusted and age-adjusted BMI metrics by the interval between the first and last examinations. The points represent the mean interval in each group.

Table 1.

Examples of unadjusted vs. age-adjusted BMI metrics among girls with a BMI that is 140% of the 95th percentile.

		Age-specific coefficients		Distance from median (kg/m^2)		% Distance from median		Log % Distance from median	
Age (y)	BMI (kg/m^2)	M (kg/m^2)	S	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
3	25.6 [*]	15.7[a]	0.079[a]	9.9	26.5	63	122	49	95
10	32.2	16.9	0.137	15.3	22.0	91	101	65	72
18	42.5	21.3	0.147	21.2	22.5	100	103	69	72
20 (reference)	–	21.7	0.153	–	–	–	–	–	–

[*] M and S are rounded from the tabulated values. The adjusted metrics are scaled to the BMI distribution at age 20 y using the values of M and/or S.

Table 2:

Descriptive Characteristics among 5628 children with longitudinal data*.

	First Examination	Last Examination	Change over time
% Girls	46%		
% Blacks	38%		
Age	7.3 ± 2.1†	13.4 ± 2.8	6.1 ± 2.7
BMI	16.4 ± 2.5	20.5 ± 4.5	4.1 ± 3.4
BMIz	0.1 ± 1.0	0.2 ± 1.1	0.2 ± 0.7
% Overweight	17%	25%	
% Obese	7%	11%	
Distance from median, kg/m^2	0.5 ± 2.4	1.6 ± 4.2	1.1 ± 2.9
Adjusted distance from median‡, kg/m^2	1.1 ± 4.5	2.0 ± 5.2	1.0 ± 3.3
% Distance from median	3.4 ± 14.7	8.8 ± 22.3	5.3 ± 14.7
Adjusted % Distance from median	4.7 ± 20.2	9.1 ± 23.2	4.4 ± 14.8
Log % distance from median	2.5 ± 12.8	6.6 ± 18.6	4.1 ± 12.1
Adjusted log % distance from median	3.5 ± 17.7	6.8 ± 19.4	3.4 ± 12.5

*The 5628 children had 18,381 examinations altogether; this table is restricted to each child's first and last examination

†Values of the continuous variables are mean ± SD

‡Adjusted using the reference values of M and S at age 20 y (Table 1)

Table 3.

Comparison of unadjusted and adjusted Intraclass correlation coefficients (ICCs) at initial examination.

	N (children / examinations)	BMIz	Unadjusted Distance: Distance from median	Unadjusted Distance: % from median	Unadjusted Distance: Log % from median	Adjusted* Distance: Distance from median	Adjusted* Distance: % from median	Adjusted* Distance: Log % from median
Overall	5628 / 18,381	0.83	0.76	0.79	0.80	0.83	0.84	0.84
BMI ≥ 85th percentile†	935 / 2923	0.62	0.54	0.60	0.59	0.71	0.71	0.70
BMI ≥ 95th percentile	373 / 1177	0.52	0.48	0.55	0.53	0.66	0.66	0.63
BMI ≥ 97th percentile	234 / 716	0.43	0.41	0.49	0.47	0.60	0.60	0.55
BMI ≥ 99th percentile	87 / 282	0.33	0.36	0.44	0.43	0.52	0.52	0.44

*Adjusted using the reference values of M and S at age 20 y

†BMI ≥ 85th percentile includes BMI ≥ 95th percentile