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Using Process Control to Measure Pediatric Obesity

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Abstract

Obesity beginning in infancy is a precursor to a life-long weight struggle and numerous co-morbidities. Thus, early diagnosis and intervention are of paramount importance. The study objectives were to use process control to produce control charts to determine and predict obesity from birth to 5-years of age.

A descriptive comparative longitudinal study using retrospective chart review of height and weight at well-child visits from birth to five years of age was conducted in a Midwestern U.S. health maintenance organization. Participants were randomly selected children (n=223) of medically-uncomplicated gestations and pregnancies, and who had no medical complications other than non-food allergies. The children were classified as either normal weight, overweight or obese at five years of age using WHO reference standards. Control charts were developed to distinguish normal, overweight and obese growth patterns using longitudinal decision analysis. Decision limits were constructed for each time point; if a child is above decision limits, the child's BMI is abnormally high with a p-value of >0.05, indicating significant difference compared to a normal value.

From 2-12 months children categorized at 5-years as normal weight were slightly below the lower decision limit, overweight children were consistently between lower and upper decision limits, and obese children were above upper decision limit. Carefully constructed control charts are a powerful method to monitor growth processes. The charts have high obesity predictive ability when used with children over 2 months old; and should be considered as a method to monitor pediatric growth.

Keywords: Pediatric obesity prediction; Body mass index; Growth patterns; Control charts; Longitudinal decision analysis

Introduction

Childhood obesity may begin much earlier in the life-course than previously believed [1-5]. Rapid growth in infancy (birth to age 2) is associated with a greater risk of later life obesity; subsequently, overweight school age children frequently become overweight adolescents [6] and, in turn, overweight adults [7,8]. Once obesity appears, obesity tends to remain throughout life [9,10]; thus, early detection and control is critical to stop the obesity epidemic.

Different reference standards are available to measure pediatric obesity; most are defined by a specific score (i.e. centile, or percentage) which is then compared to a growth threshold limit indicating weight status [11]. The commonly used reference standards to determine pediatric obesity classifications are: Centers for Disease Control (CDC) weight-for-length growth charts [12], World Health Organization (WHO) Body Mass Index charts [13], and the UK90 BMI reference centile curves [11]. Modeling of infant BMI trajectories, weight gain trajectories, weight-for-length growth patterns, early rapid growth, and adiposity rebound have all been suggested as both growth reference standards and predictors of later life obesity [14-18]. Obesity risk prediction scores utilizing infant weight gain in the first year, birth weight, gender, race, mother's (pre-pregnancy) BMI and paternal BMI have also been proposed as methods to predict later life obesity [19, 20]; obesity risk scores are not fully developed and are not used in clinical practice. However, there are no tools that measure both current and predict future infant obesity.

We applied statistical process control techniques to develop control charts of infant growth that could present a way to measure current and predict future obesity in infants. Statistical process control using control charts allows visualization of a process such as growth that includes variation. When variation is present, upper and lower decision limits determine if the variation is naturally normally occurring. Process control is widely used in laboratories to detect changes in the quality of routine analytical measurements and is used on the manufacturing assembly line to assure that processes are under control. Process control has been transferred from the manufacturing assembly line to the 'process' of animal growth in agriculture and is used to indicate if animals are either growing within normal growth parameters or producing milk/ eggs within normal quantities with a statistical level of confidence [21]. Use of Control charts is a precise and accurate growth monitoring and prediction tool for cow, turkey and pig growth [21]. Control charts are a quick and easy way to detect occurrences/ trends/ growth patterns that are either not normal or trending towards normality so early intervention can occur.

The study objectives were: 1) describe the upper and lower decision limits for a normal pediatric growth pattern over the first five years of life using longitudinal decision analysis to create a normal human growth control chart; 2) determine if the derived control charts could determine current obesity status; and 3) determine if the derived control chart could be to predict future pediatric obesity status (normal, overweight, obese) up to five years of age.

Materials and Methods

Only healthy children were included in the sample, which differs from other studies. Previous studies of large data bases have included

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children, who could have been ill or injured, both of which could change growth patterns [22-26]. The sample data were obtained from a United States Health Maintenance Organization (HMO) in the Midwest after Institutional Review Board approval. A longitudinal retrospective chart review was conducted. Current studies of weight-for-length or BMI trajectories have had limited data points, i.e. 2 [18], 4 [18], and 6 [14] in the first five years and 8 over the first 14 years of life [27]; limiting their ability to discriminate differences between weight classifications within the first year of life. To correct this limitation, we extracted data for birth and well-child visits (1-week; 2-, 4-, 6-, 9-, 12-, 15-, 18 months; and 2-, 3-, 4- and 5 years) and from the child's mother's antenatal clinic records, yielding 8 data points in the first 18 months of life and 12 data points over 5 years.

Inclusion criteria were: complete medical records for pregnancy, birth, and at least 8 of 12 well-child visits between birth and 5-years. The children had to be healthy (five minute APGAR of 8 or more), of singleton birth at term age (gestation ≥ 38 weeks) after an uncomplicated pregnancy, Appropriate Weight-for-Gestational Age at birth and have no medical complications other than non-food allergies, and not classified as underweight at age 5 (< 25 percentile as defined by WHO BMI criteria [13]). Additionally, the mother could not have pre-pregnancy nor, gestational diabetes.

Charts were predominantly excluded because either the child or maternal antenatal records were incomplete. The HMO had approximately a 30% annual patient turnover rate; hence, many subjects were excluded because their charts did not have the requisite number of well child visit records. Excluded infants had similar demographic characteristics as those included.

Forty thousand mother-child chart records were screened by a computer-generated algorithm based on the inclusion criteria. The computer randomly selected 400 records of 5 year old children, with half below and half above the 95th BMI percentile (i.e. the cutoff for obesity). Charts were then manually reviewed for inclusion criteria, yielding 223 valid records. Three data collection teams were trained to ≥ 0.80 reliability agreement on sample criteria and data extraction procedures. The children's charts were then grouped into cohorts by their obesity status at 5-years (i.e. normal-weight (n=61) BMI ≥ 25th to < 85th percentile, overweight (n= 47) BMI ≥ 85th to < 95th percentile, or obese (n= 115) BMI ≥ 95th percentile categorized by WHO criteria [13].

The child's age was measured as 'months since birth' so data at each 'well-child' visit could be easily compared over time. Because children rarely were seen on the exact day of the expected well-child visit, the mean age in days of the child on the date of each well-child visit was converted to months and used to develop the control charts. Age was then parameterized in months since birth for each time point similarly to the procedure used in development of the WHO growth curves [13].

Sample size using Cohen's analysis [28] for determining group differences, with power =0.80; a medium effect size = 0.50 (equivalent to 0.5 BMI) and α=0.05 yielded 51 subjects for each cohort. The study was slightly underpowered for the overweight and obese cohorts, but Cohen (1988) has shown that overall, a study can be underpowered for any single test in a repeated measure ANOVA and ANOM, but the overall study could still have significant results [28,29]. For repeated measure statistical analysis, the power for a specific comparison is different than the power for any and all pairs; the study is slightly underpowered for prediction detection of a specific comparison, but, the study is adequately powered to detect all statistically significant results [29]. For example, in order to detect all non-zero effects with a power of 0.80, the study needs 51 subjects per cohort; but, the probability of obtaining at least one statistically significant result overall with a power of 0.80 can be detected with a smaller sample of 30 subjects per cohort [29].

A normal growth control chart was developed from the BMI values of the children who were normal weight at 5 years using analysis of means (ANOM) [30]. Longitudinal decision analysis anticipates that an individual's BMI values would fluctuate randomly about the average normal BMI value until such time as an infant's growth changes; once change occurs, it is possible to distinguish growth patterns [30]. When a child's BMI is above the upper decision limit (UDL), the child's BMI is abnormally high with a p-value of >0.05, indicating significant difference compared to normal values. When a child's BMI is below the lower decision limit (LDL), the child's BMI is abnormally low with a p-value of >0.05.

To assess the control chart approach, ANOM was used to compare the averages from each of the three cohorts. ANOM is a graphical procedure for comparing a collection of means to determine if any of them differ significantly from the reference standard; it is a multiple comparison procedure with the results summarized in an ANOM decision chart, having a centerline, located at a hypothesized mean, and lower decision limit (LDL) and upper decision limit (UDL). A variable's value (i.e. BMI) over time is plotted on a control chart that identifies LDL and UDL [31].

Many statistical quality improvement applications involve a comparison of treatment means to determine which are significantly different from the overall average. As a statistical technique, an analysis of means (ANOM) is an alternative to one-way analysis of variance (ANOVA) for a fixed effects model. However, unlike ANOVA, which simply determines whether there is a statistically significant difference in the treatment means, ANOM identifies the means that are significantly different from the overall mean. Regressions were not performed because the study tried to determine if human infant growth could be measured, tracked and categorized as "in or out of control"; in or out fo control growth signified either in control growth (i.e. growing within normal ranges) or out of control growth (i.e. growing outside of normal ranges-overweight or obese growth). Whenever averages are compared, ANOM is preferred rather than one-way Analysis of Variance (ANOVA) because the results are easier to interpret due to the graphical representations available in ANOM when there are unequal numbers of observations per group. When there are more than two standard deviations being compared, the test for homoscedasticity can be performed using ANOM and analyzed graphically which is more revealing than a Bartlett's test when the null hypothesis is rejected [31]. Analysis of means lends itself to quality improvement applications because it has a simple graphical representation. We assessed the practical significance of the control chart method of tracking infant growth.

The decision limits for the ANOM were the average of BMI for the normal cohort since the objective was to detect overweight or obesity at the earliest age when intervention could occur to address this condition. The standard deviation used was weighted root mean square standard deviation base on all three cohorts to maximize the degrees of freedom for estimating dispersion in BMI [32]. Normal growth limits for average BMI were designed with the UDL (p – value 0.95) and LDL (p–value 0.05) at each time point. The average BMI for each time point by cohort was then plotted on the derived control charts.

Results

Gender was almost equal in the cohorts, overall 49.5% males and

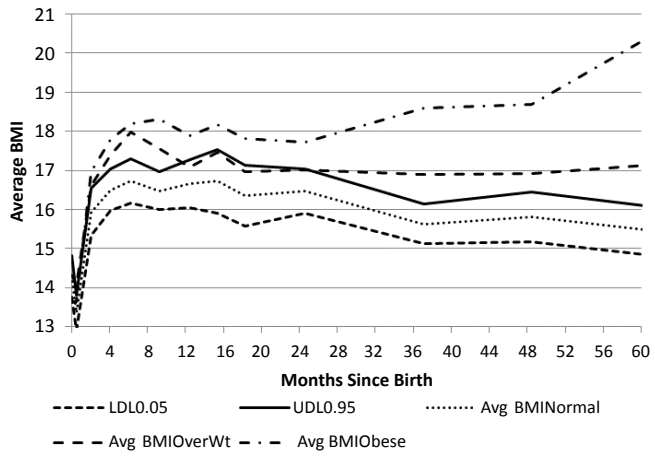

Figure 1: Control chart UDL and LDL for a male from birth to 5 years old based on normal cohort for monitoring individual's BMI in order to detect the onset of overweight or obesity at the earliest age possible.

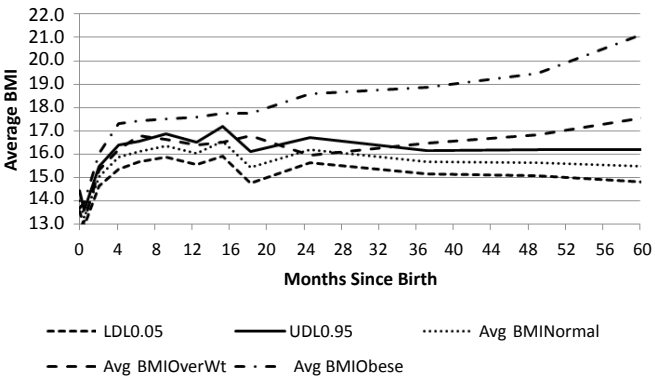

Figure 2: Control chart UDL and LDL for a female from birth to 5 years old based on normal cohort for monitoring individual's BMI in order to detect the onset of overweight or obesity at the earliest age possible.

50.5% females (48% male in normal; 53% male in overweight; and 49% male in obese). The birth was considered as 0 months, and mean age in months since birth for each cohort as the x-axis point for plotting in the control chart graphs. Figures 1 and 2 present the male and female control charts indicating the relative position of the LDL and UDLs from birth to 5-years based on the normal cohorts average BMI using 95% confidence limits. We pooled the variances by weighting them based on df to smooth the curves (Figures 1 and 2).

Before 2-months, all cohorts fluctuated between the control chart LDL and UDL. At 2 months, a clear departure from normal growth occurred in the overweight and obese cohorts; both crossed the UDL and remained above the UDL thereafter. The crossing of the UDL is an indicator of out of control growth. Afterward, the average BMIs for the overweight and obese cohorts are above the UDL for the normal cohort while the normal cohort primarily plots between the LDL and UDL (Figures 3 and 4). The sensitivity was 83% for the obese cohort and 58% for the overweight cohort.

Another way to visualize the discriminating power of the ANOM was to use the arithmetic average of BMI for each cohort as the null hypothesis. Clear differences can be seen between the mean cohort BMI and the respective LDLs/ UDLs (Figure 5), significant differences ($p \leq 0.05$) in BMI were present between all cohorts at 2- ,6-, 12- months and 5-years. At each time point, the mean BMI of the obese cohort was above UDL, mean BMI of the overweight cohort was between LDL and UDL, and mean BMI of the normal weight cohort was less than LDL.

Discussion

Because humans and their environment can be considered a system controlled by various processes, it is a reasonable to approach pediatric growth using control charts based on BMI values as a time ordered series of observations. Examining the data in the order in which the data were observed is critical because only then can trends, cycles, and other non-random characteristics be detected. A signal on a control chart such as a BMI outside the UDL shown in Figures 1 and 2 signifies a diagnosis that the individual's growth is trending toward later life obesity, which then leads to finding the root cause(s) for the out-of-control value [21]. The underlying causes of a child exhibiting a non-normal (i.e. obese growth pattern) need to be explored so their growth can be re-directed back into a normal pattern.

Our findings concur with other research showing that children who crossed more than two weight-for-length percentile lines on CDC growth charts in the first 6 months of life had the highest risk

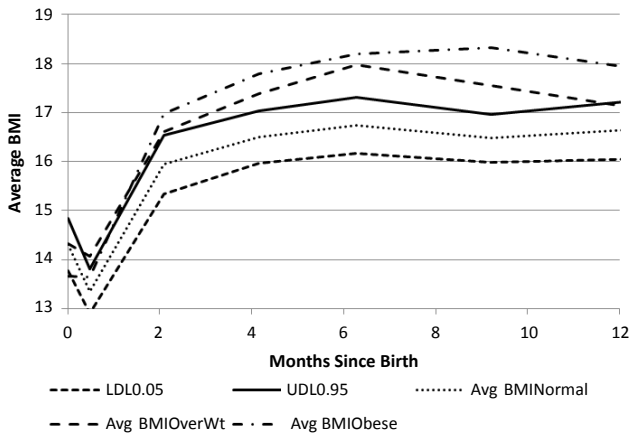

Figure 3: Control Charts (with normal cohort average UDL and LDL) and the average BMI for males from birth to 1 year old and expanded chart showing from birth to 2 years from all three cohorts in the study.

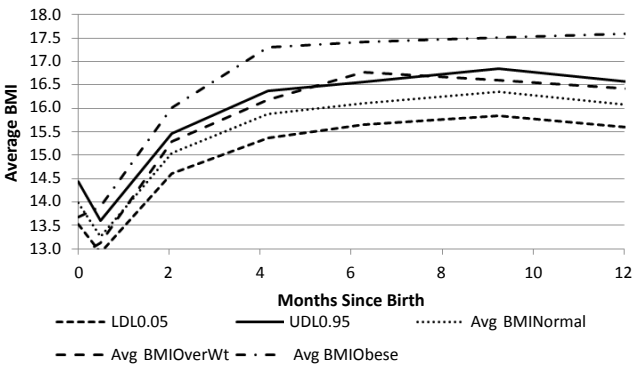

Figure 4: Control Charts (with normal cohort average UDL and LDL) and the average BMI for females from birth to 1 year old and expanded chart showing from birth to 2 years from all three cohorts in the study.

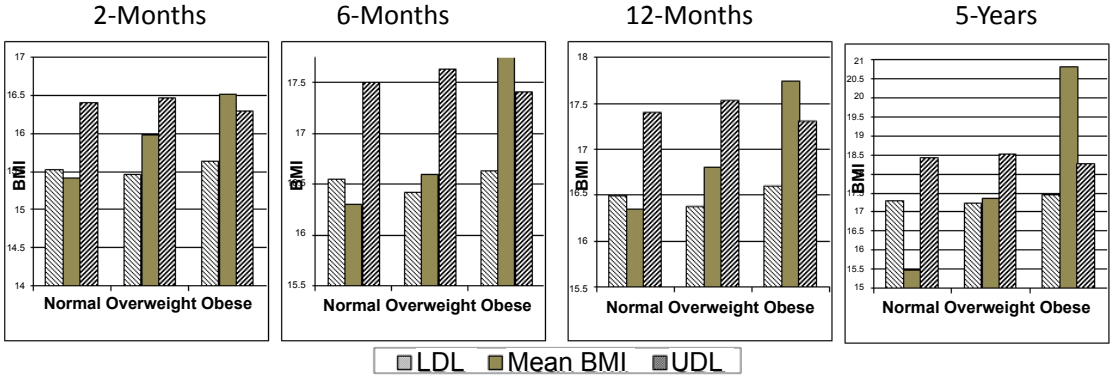

Figure 5: Two-, Six-, Twelve months and Five-years ANOM for Mean Cohort BMI plotted with LDL and UDL based on an average of all three cohorts. An average less than the LDL indicates that the average is significantly less than the overall average and a value greater than the UDL indicate that the average is significantly greater than the overall average of the three cohorts for an overall p – value of 0.05.

of being obese at 5-years [18]. We found that we could predict both development of overweight and obese growth patterns/processes in the first 2-12 months; the control charts could both diagnosis current obesity and predict obesity at five years. By 2 months, the control charts could distinguish out of control growth in the overweight and obese cohorts; it was apparent that growth in the overweight and obese cohort was outside of a normal growth process. The control charts provide an easy metric to determine when an infant is growing outside of normal ranges and predicts future obesity. Control charts provide an easy to use infant growth tracking mechanism for providers to determine if a weight-control intervention is necessary. Our data confirm previous reports that BMI pattern in the first year can differentiate children who will become obese from those who will not become obese later in life [1,24,33]. Our results are also consistent with reports that appropriate weight-for-gestational age children who display rapid weight gain in infancy have a greater risk of being overweight or obese during childhood than children who did not experience rapid weight gain post-birth [34].

Control charts are superior to growth charts or obesity risk scores for obesity risk prediction because a continuous indicator of pediatric growth is better than a singular specific threshold [19]. Control charts are based solely on the individual child's data which should be readily available at well-child visits as compared to obesity risk scores which need parental data. Control charts monitor the process of infant growth irrespective of SES, racial, ethnic and parental factors which can be inconsistently measured and have wide variability even though they are used in other obesity risk prediction tools [20]. Controls charts allow for an accurate and calibrated method that has widespread validity that is not subpopulation dependent. Control charts allow visualization of a process, such as growth, that includes variation [31]; by examining the extent of the variation from average or normed growth trends, cycles, and other non-random characteristics of the processes that can be easily recognized. The Predictive aspect of control charts will facilitate meeting the Institute of Medicine's recommendation that regular growth monitoring and consideration of obesity risk during infancy be undertaken [35]. Control charts such as those shown in Figures 1 and 2 should be seamlessly integrated into the routine of a well-child visit for both diagnosing current obesity and predicting future obesity in infants.

Current efforts are underway to incorporate obesity prevention programs into young children's well-child visits [36]. Providing an obesity prevention program to all children is not cost effective due to the cost and the time constraints of well-child visits. We recognize that there are concerns with diagnosing obesity in infancy. However, use of control charts will provide a mechanism to discriminate which infants actually need an intervention and will allow for easier monitoring by clinicians. Employing focused strategies involving infants whose obesity risk is high according to a calibrated growth tool such as a control chart, allows targeting interventions to only those who need it. Control charts may lead to earlier, more effective prevention of overweight/ obesity in children [20]. The study demonstrates that onset of an obesity growth pattern early in life can be detected and predicted by control charts that has decision limits based on a healthy population of infants/children.

Studies of childhood growth are increasing, revealing that rapid growth in infancy is associated with a greater risk of later life obesity [7,8]. Predicting obesity at 5-years is important because obesity at 5-years predicts adult obesity [10,37,38] and co-morbidities [39-45]. Early development of obesity leads to longer duration and impact of co-morbidities [46]. In addition to raising healthcare costs, over $14 billion annually in the U.S.[47], the early onset of obesity is a precursor to a life-long weight struggle [10] and numerous co-morbidities such as cardiovascular disease [45], hypertension [48], diabetes [49], osteoporosis [50], and hip damage [51].

Limitations

The study was a pilot study to confirm sensitivity and specificity of the derived control charts, a much larger sample will be needed for validation. The longitudinal decisional analysis procedure is relatively simple but, the model does not address the inherent multicollinearity of the measurements, thus, the observations of an individual child are potentially correlated; again, a larger study is called for to confirm sensitivity and specificity found in this report of control charts. The small sample size limited statistical analysis. The study was underpowered for multiple regression analysis but not underpowered for the process control analysis, ANOM, however, significant differences have already appeared before 2-years of age, so confirmation with a larger sample is needed. Gender differences that affect growth and obesity development occur early in life [33], thus, as we continue refining the control charts we will explore the necessity for gender specific charts. Thus, confirmation of the control chart decision limits described here in a larger study is indicated.

Conclusion

There is no growth chart, scale, or score currently in use that can

distinguish normal weight growth from obesity growth in infants and predict future weight status. Measurement of a healthy cohort of infants and children birth to five years provided the seminal data needed to establish control charts to delineate three classifications of weight: normal weight, overweight, and obese. The control charts also predicted age 5 obesity as early as 2 months. Confirmation of upper and lower decision limits with a population-based sample of healthy community dwelling infants and children is needed so that control charts can be used to classify current weight statuses and clinically predict risk of later obesity. Once a pattern that predicts obesity has been determined, examination of and intervention related to nutrition, exercise, sleep, and family environment can be pursued, beginning with the provision of breast milk feedings which is an easily applied early life intervention [52].

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