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Exploring categorical BMI trajectories in elementary school children

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Abstract

BACKGROUND—Studies of body mass index (BMI) change have focused on understanding growth trajectories from childhood to adolescence and adolescence to adulthood, but few have explored BMI trajectories solely in elementary (grades K–5) school children. This report complements these studies by exploring changes in obesity status using analytic methods developed to investigate categorical changes in life course events.

METHODS—Sequences of a 4-state BMI variable (underweight, normal, overweight, obese) were calculated using height and weight data collected annually (2008–2013) from 414 kindergarten and first grade students participating in the Community and Schools Together (CAST) project. These sequences were explored using the TraMineR software package to investigate the distribution of sequences and states, calculate transition rates among states, and examine clustering of sequences.

RESULTS—Aggregated cluster solutions were identified consisting of either 4 clusters (normal, stepped, mixed, obese) or 3 clusters (aggregation of obese cluster cases into stepped cluster) with membership in the former predicted by ethnicity and socioeconomic status (SES) and the latter by SES alone. Transition rate patterns among states varied markedly by cluster and state.

CONCLUSION—The finding of early emergence of stable obesity states, especially in Hispanic children confirms the need for early childhood interventions to influence BMI.

Keywords

body mass index; developmental trajectories; overweight/obesity; elementary school

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Overweight and obesity in childhood and adulthood are complex conditions that develop from the interaction of genetic, metabolic, social, behavioral, and cultural factors.^{1,2} Childhood overweight and obesity continue to be a major concern and focus of public health efforts in the United States (US). Significant increases in obesity prevalence for children and adolescents occurred during the 1980s and 1990s, although there have been fairly recent reports of stabilization and, in some cases, declines in prevalence.³⁻⁵ However, obesity continues to be recognized as a major problem in childhood and a recent study indicates there is an upward trend of more severe forms of obesity.⁶ Additionally, obesity in childhood may track into adulthood.⁷⁻⁹ In one of the largest studies of its kind, researchers found that adult obesity could be traced back to weight at as early as pre-kindergarten, much earlier than had been previously thought.⁷ The health risks associated with overweight and obesity in childhood include early onset of type 2 diabetes, asthma, obstructive sleep apnea, and psychological distress.¹⁰⁻¹²

One important recent research theme in the childhood obesity literature has focused on the developmental trajectories of weight change during childhood and adolescence. Such life-course approaches offer valuable insights into the heterogeneity in weight gain over childhood and adolescence and subsequent consequences for related chronic diseases.¹³⁻¹⁵ Additionally, information about the timing of weight gain may be helpful for the development of effective interventions.¹⁶ A number of studies have focused on body mass index (BMI) change from childhood to adolescence or adolescence to adulthood and have highlighted the importance of understanding growth trajectories.^{13-15,17-24}

However, as seen in Table 1 only a few studies have focused on BMI growth trajectories solely during childhood.^{11,16,25-27} Balesteri and Van Hook¹⁶ modeled prevalence of overweight and obesity in the Early Childhood Longitudinal Study-Kindergarten Cohort (ECLS-K) from K to 8th grade. They identified 3 trajectories: normal, always overweight/at risk of overweight, and gradually becoming overweight/at risk for overweight. These researchers found some evidence that low parental income and education were both significant risk factors for the gradual onset of overweight in girls but not for boys. They also found children of immigrant parents were more likely to experience early and sustained overweight throughout elementary and middle school. This was particularly common for boys. Similarly, Lane et al,²⁵ examining psychosocial factors such as parenting style and maternal depression, used growth mixture models to identify distinct subtypes of BMI development. They identified 3 prototypic trajectories of BMI percentile growth: elevated, steady increase, and stable. They found BMI development was related to SES, maternal depression and maternal parenting styles.

Li et al¹¹ tracked a sample of children from ages 2 to 12 years and identified 3 trajectories, representing early onset, late onset and never overweight. They further determined that early onset overweight was more likely in boys, African Americans, those with overweight or obese mothers, those whose mothers had higher pregnancy weight gain, and those with higher birth weight. Following a sample of Australian children from age 4–5 through age 10–11, Magee et al²⁶ identified 4 distinct developmental trajectories using raw BMI values: high risk (overweight), early onset overweight, later onset overweight, and healthy BMI. They also found that socio-demographic factors such as mother and father overweight/

obesity, education, smoking, and child birth weight were significantly related with these trajectories. They proposed that their results may suggest commonalities among BMI/obesity trajectories in different samples of children and that interventions could be tailored specifically towards at-risk trajectories. Pryor et al²⁷ identified 3 trajectories: low stable, moderate, and high rising. Their analysis indicated children on an elevated BMI trajectory could be distinguished from children on a normative BMI trajectory as early as age 3.5 years.

The purpose of this study was to examine the trajectories of BMI categories in elementary school children using analytic methods developed for studying categorical changes in life course events. The analysis examined clusters of trajectories to test for differential association with selected covariates. A secondary goal was to augment current research by comparing the results with growth trajectories identified in other studies that used traditional analytic methods.

METHODS

Participants

The data for this study were collected during the Community and Schools Together (CAST) project. CAST was a federally funded 5-year community-based participatory research study that examined the environmental and social influences on the prevalence of child overweight and obesity in a suburban Oregon school district.²⁸⁻³⁰ In the first year of the CAST project, during fall of the 2008–2009 school year, all families of children in grades K–5 who attended any of 7 district elementary schools were sent a description of the CAST project by mail. Included with the description was a passive decline or “opt out” card. In each of 4 subsequent school years, these materials were sent to all families with children entering kindergarten (K) as well as families of students in grades K–5 who had transferred into the district. District staff assigned a study ID to all participating students. Across the 5-year period, BMI data were collected for 5046 students representing 11,116 measurements during the project. The study design followed students only through elementary school with planned missingness after grade 5. A single measure was collected for 1847 students, while 1286, 869, 630, and 414 students had measures at 2, 3, 4 or all 5 time points respectively.

Measures

School record data—Child characteristics used in this study, extracted from the district data system, included sex, age, school, grade, ethnicity, race, and eligibility for free and reduced lunch (a proxy for SES). Home addresses were used to construct a household (family) ID, and to calculate the number of elementary school siblings for each participant.

BMI—Height and weight data for each child were collected in conjunction with the district's annual health screening. Measurement procedures were consistent with standardized anthropometric procedures. All data were recorded directly on the district health screening forms. Height and weight data were transferred to the CAST project database for data management and analysis. The Epi Info (US Centers for Disease Control, Atlanta, Georgia) analysis tool, NutStat, a nutrition anthropometry program that calculates BMI from age and

sex normed tables, was used to calculate raw BMI, z-score, and percentile equivalents. BMI categories were calculated using the BMI percentile scores—underweight (u), < 5%; normal (n), 5% & < 85%; overweight (ov), 85% & < 95%; and obese (ob), 95%).

Data Analysis

Analytic approach—Common approaches to analyzing change over time in data include latent class analysis (LCA) and sequence analysis (SA).³¹ LCA is a parametric modeling approach that assumes that individuals belong to a finite set of unobserved classes (ie, latent classes). SA is a nonparametric data-mining technique that determines pairwise distances among sequences. LCA is more commonly applied to continuous data, whereas either LCA (using a logistic link function) or SA can be applied to categorical values.

The analysis for this paper examined BMI trajectories using categorical SA for several reasons: (1) BMI categories are commonly used to summarize ranges of BMI percentile scores in educational settings; (2) the approach facilitates easy identification of changing sequence patterns across time; and (3) the focus on individual sequences of states as the unit of analysis provides an additional tool for understanding changes in BMI.

Sequences consist of values stored as ordered arrays where the order of each value is important (ie, a sequence can represent a series of states over time). Using sequence as the unit of analysis requires appropriate analytic tools. We used the statistical and graphing tools provided in the trajectory mining package, TraMineR,³²⁻³⁴ a package for the R statistical computing environment.³⁵ TraMineR provides functions for describing and plotting sequences, calculating temporal transition probabilities among states, calculating dissimilarity matrices, as well as support for tree-structured ANOVA analyses.³⁶ Many of these functions are analogous to analytic tools used to assess continuous measures. In cases where this is not obvious, the sequence method is described in the text. The process of classification is *exploratory*, with relationships to predictor covariates analyzed by using sequence groups as a response variable in regression models.

Trajectory analysis sample, covariates, and analyses—Of the 5046 students, 414 had all 5 observations. In light of the exploratory nature of the analyses, these sequences, representing the complete trajectories for students in kindergarten and first grade at the time of the first observation, were used for the analyses. Table 2 lists the variables included in the sequence analyses. The covariates, ethnicity, free and reduced lunch, and presence of elementary school sibling, are those shown to be significant predictors of being overweight/obese in earlier analyses.²⁹ Comparison of the 414 sample of students to those students with 4 or fewer observations (N = 4632) showed that only eligibility for free and reduced lunch as a proxy for SES was significantly different (32% for 414 group and 50% for 4632 group—chi square 45.31, df=1, p < .001). This difference is similar to an earlier finding that the CAST sample had a higher SES than was characteristic of the whole.²⁹ Thus, the sample used here is not representative of the district in terms of the proxy SES variable of free and reduced lunch eligibility.

At the time of the first observation, a majority of the 414 students were Caucasians (N = 314, 76%), followed by Hispanics (N = 62, 15%), and African Americans, Asians, Native

Americans, or Native Hawaiians or Other Pacific Islanders ($N = 38$, 9%). Thirty-two percent of students were eligible for federal meal subsidies ($N = 133$). Approximately half of the students were first observed as kindergarteners ($N = 200$, 48%) and half as first graders ($N = 214$, 52%). Approximately half the students had no elementary school siblings (219, 53%), and 195 (47%) had one or more siblings.

Sequences were first described in terms of their salient characteristics (eg, frequency, distribution, time in state). Next the relationships among sequences were explored using bootstrapped, aggregated 4-cluster and 3-cluster solutions based upon a distance matrix determined via Optimum Matching (OM).³⁶ The OM method calculates the pairwise dissimilarities among sequences by determining the cost of transforming one sequence into another, where cost is based on the number of substitutions and deletions/insertions required to transform the sequences. Logistic regression was used to assess prediction of 3-cluster and 4-cluster membership by the covariates. Finally, analyses using an analog to traditional analysis of variance and a regression tree approach were conducted to assess the effect of predictors upon the distance matrix.

RESULTS

Sequence Characteristics

Sequence frequency and distribution—The 414 cases contain 73 unique trajectories, of which 3 account for 67% of the cases; these 3 trajectories are: (1) all 5 time points normal ($N = 216$, 52.2%); (2) all time points obese ($N = 52$, 12.6%); or (3) all time points overweight ($N = 12$, 2.9%). Of the 2070 (5×414) time points observed, 1 % were underweight, 64% were normal, 15% were overweight, and 19% were obese. The 10 most common sequences accounted for 78.5% of all cases. There was a general increase in obese and overweight states across the 5 measurement occasions. Fifteen percent of children were first observed as overweight ($N = 63$) and 16% were obese ($N = 68$). The proportion of obese children (19%) increased relative to normal and underweight children over the 5 years. The proportion of overweight children remained relatively constant (~15%).

Transition rates—Table 3 gives the probability of moving from state i at time t to state j at time $t+1$. Transition rates among all states were calculated, the diagonal values indicating more stability for those in normal or obese categories (ie, a child was likely to stay within his or her BMI class between any 2 sequential time points). Normal weight children were most stable, partially reflecting the broad range of BMI values that the state covers. These transition rates reflect the general movement towards overweight and obese states over time. Underweight students were about 1.5 times as likely to transition to normal weight (0.61) as to remain underweight (0.39). Normal weight students were likely to remain so (0.92) with most transitions being to overweight (0.06) or, to a lesser extent, underweight (0.01) and obese (0.01). Overweight students were likely to stay in the state (0.60) and about 1.5 times as likely to transition to the obese state (0.24) as to normal weight (0.16). Finally, students in an obese state were likely to stay in the state (0.87), with a low probability of moving to an overweight (0.10) or normal state (0.03). These transition rates were arranged in a matrix

and used as input to the OM algorithm for forming a paired distance matrix for the sequences.

Cluster Analysis

Cluster description—To assess similarities among sequences, both 3-cluster and 4-cluster solutions were created using agglomerative hierarchical clustering (Ward criterion).³⁷ Both solutions produced strong structures with an Average Silhouette Width (ASW) above .7.³⁸ The 3-cluster solution (ASW = .74) consisted of (1) normal, (2) mixed, and (3) stepped clusters. The normal trajectory cluster (N = 264, 63.8%) contained individuals who stayed in a normal BMI state, or deviated without direction into and back from underweight and overweight states. The modal sequence for this cluster was a normal state at all 5 time points, representing 82% of the cluster members. The mixed trajectory cluster (N = 60, 14.5%) students fluctuated between states with a modal sequence of overweight (20% of cluster members). In the stepped trajectory cluster (N = 90, 21.7%) students moved from overweight to obese across observations with 58% of the cluster cases represented by an obese state across all 5 years.

The 3-cluster solution resulted from aggregation of a 4-cluster solution (ASW = 0.72), in which the fourth trajectory cluster obese consisted of cases (52) that were obese at all time points. In the 3-cluster solution, these cases were allocated to the stepped trajectory cluster. The normal and mixed trajectory clusters were identical in both solutions. The reduced stepped trajectory cluster (N = 38) in the 4-cluster solution consisted of students who moved from overweight to obese across observations with 13% of the cases represented by a modal sequence of overweight in the first 2 years followed by 3 years in an obese state. Figure 1 shows the state distributions across time for the 3- and 4-cluster solutions.

Cluster entropy—The variability in states in the 4-cluster solution was measured by sequence entropy, which depends upon the extent to which states in a sequence vary across time. Entropy remained low for normal and obese trajectory clusters. The mixed trajectory cluster showed a decrease and then an increase in entropy. The stepped trajectories for both the 3-cluster and 4-cluster solutions decreased over time, reflecting a convergence toward the obese state.

Cluster transitions—The transition probabilities of the states in each of the clusters for both the 3-cluster and 4-cluster solutions indicate only the stepped trajectory cluster transition rates for obese cases differ between the 2 solutions (Table 3). The normal trajectory cluster transition probabilities were similar to those for the whole sample for underweight and normal cases, while transition to a normal state from an overweight state (0.65) or an obese state (1.00) was much higher than that for all the cases.

In the stepped 4-cluster group, children were approximately twice as likely to transition from overweight to obese (0.66) than to remain in an overweight state (0.34), while obese cases were approximately 3 times as likely to stay obese (0.75) as to move to overweight (0.22). In the 3-cluster solution, where obese cases have been added to the cluster, the probability of remaining obese rises to 0.93. The mixed trajectory cluster shows that cases are 9 times as likely to go from obese to overweight states (0.93) than from overweight to

obese (0.11). Finally, there is only one state in the obese cluster for the associated cases in the 4-cluster solution (1.0).

Prediction of Cluster Membership

Logistic regression analyses predicting cluster membership from the covariates were conducted for the 3-cluster and 4-cluster solutions. For the former, only eligibility for subsidized meals was significant (OR = 1.97, 95% CI [1.29, 3.02], $p < .002$). For the latter, 2 significant predictors, ethnicity (OR = 2.46, 95% CI [1.40, 4.35], $p < .0002$) and eligibility for subsidized meals (OR = 2.29, 95% CI [1.49, 3.53], $p < .007$) were identified.

Analysis of Variance/Regression Tree

The results of conducting a nonparametric, permutation driven, multiple ANOVA (Type II effects—effect of predictor with all other predictors entered; overall Psuedo-F = 4.133, Psuedo-R² = 0.0482, $p = .001$) on the distance matrix using sex, meal subsidy, ethnicity, and sibling status at first observation indicate 2 significant predictors, ethnicity (Psuedo-F = 0.3704, $p = .009$) and eligibility for subsidized meals (Psuedo-F = 8.497, $p = .001$). This confirms results found in analysis of the first year's data,²⁹ while a third predictor, presence of siblings, was not confirmed.

Figure 2 shows a regression tree for the same set of predictor covariates with a criterion of $p = .01$ for including a predictor as a split variable. In this approach, the predictor that accounted for the greatest part of the discrepancy among the sequences (ie, highest pseudo-R²) was chosen as the split variable for the node. Tree branching stopped at the point where there was a nonsignificant pseudo-F for the selected split. The first split on the diagram indicates a pattern of higher overweight and obesity among the children who are recipients of free or reduced lunch (low SES proxy). Of particular importance, the tree diagram highlights the early and consistent sequence of obese states for Hispanic students with low SES. This pattern appears to begin before entry into elementary school.

DISCUSSION

One important contribution of our study is the sequence frequencies of BMI trajectories. Yearly percentages for obesity increased over the period of the study. Fifteen percent of children were first observed as overweight ($N = 63$) and 16% were obese ($N = 68$). The proportion of obese children increased relative to normal and underweight children over the 5 years, whereas the proportion of overweight children remained relatively constant (~15%). This finding differs from that of Lohrman et al.,¹⁹ who found, within relatively short time periods, child and adolescent BMI status moved substantially in both desirable and undesirable directions, especially among overweight and obese categories. Generally, in terms of transitioning from one category to another, children were 6 times more likely to move into a higher BMI class than a lower one. Similarly, overweight students were 1.5 times more likely to rise into the obese class than drop to normal. These transitions rates reflect the general movement towards overweight and obese states over time. A similar trend was found by YoussefAgha et al.²⁴ Children in the normal BMI category were the most stable, partially reflecting the broad range of BMI values in that state.²⁴

A summary review of those studies focusing on trajectory analysis (Table 1) indicated that the trajectory patterns and number of trajectories varied among the different studies, reflecting differences in analytical methods, sample selection, and the objectives of the specific study. In general, however, all of the studies identified a group, regardless of what it was named, that included those children who had a BMI in the normal category and did not change over time. In the current study this trajectory accounted for close to two-thirds of the sample (63.8%), indicating that many children in the study exhibited a low risk of obesity during the developmental period of elementary school period. Whereas it is possible that some of these children might become overweight/obese at a later age, we were unable to determine this in the present study. The other categories in each study reflected some pattern of change, primarily moving toward overweight or obesity.

In the current analysis, using sequences of categorical states based on BMI percentile scores, 3-cluster and 4-cluster solutions identified trajectories comparable to those in several of these studies. For example, in the 4-cluster solution the different groups (normal, obese, mixed, stepped) map closely to those of Magee et al²⁶ (Healthy, High Risk, Late Onset, Early Onset) for a comparable age range. This is interesting given Magee et al²⁶ use raw BMI value as a measure of adiposity, a larger sample size, differing distribution of cases across categories, and a parametric approach to modeling. Like Magee et al²⁶ we found no relationship of trajectories to sex. Similarly, the trajectories identified by Lane et al²⁵ (elevated, steady increase, and stable) as well as those from Li et al¹¹ (Never, Early onset, Late onset] and Balesteri and Hook¹⁶ (Normal, Gradually becoming overweight, Always overweight/risk of overweight) appear similar to the normal, stepped, and obese clusters from the 4-cluster solution reported here.

Findings from our analyses suggest that both the normal and obese groups remain stable over the 5 years of the study period indicating that children who enter kindergarten as normal or obese are likely to remain that way throughout elementary school.

In both of the cluster solutions the mixed cluster shows the most variability over time and includes children who experience a decrease in weight status during the 5-year period. As indicated above, the mixed cluster shows that cases are 9 times as likely to go from obese to overweight states (0.93) than from overweight to obese (0.11). Whereas this ratio is encouraging, being overweight is still indicative of potential health risks. The stepped cluster, in both solution, reflects a convergence toward an obese state over the elementary school period and suggests a pattern of high risk for obesity. The obese group, in the 4-cluster solution demonstrates considerable stability over the period of the study, a finding of concern since it is characterized by early onset and continuation throughout the elementary school period. When the obese category from the 4-cluster solution was aggregated into the stepped category of the 3-cluster solution it represents 22% of the study sample either moving toward obesity or being classified as obese during the 5 years of elementary school. The inclusion of the mixed category (14.4%) makes the number of children in the population who are considered either on an overweight or obese trajectory at any point in the elementary school period alarmingly large (36.2%).

Whereas our results did not reveal statistically significant sex differences in trajectory patterns, this may be due to the developmental age of the sample, which is primarily prepubertal. The results, however, do highlight distinct trajectories between Hispanic and non-Hispanic children. Additionally, the finding of an earlier emergence of obesity in Hispanic children has been identified in other studies,^{16,42} particularly for first generation immigrant families characteristic of our study's Hispanic children. This consistent finding, especially considering that these studies used different methods, appears robust and is important for understanding disparities in BMI.

Limitations

Limitations of this paper include sample size, physiological characteristics associated with BMI trajectories, and the exploratory nature of the analyses employed. The small N of 414 resulting from a focus on complete cases for those first measured in kindergarten or first grade omits information about trajectories starting at a later age. Secondly, the study relies on BMI measurement procedures developed assessing student height and weight at annual intervals. The omission of direct measures of changes in child visceral or subcutaneous body fat or lean body mass reduces the certainty of the accuracy of the study's cases assigned to the mixed, stepped, and obese trajectories. For clinical interventions, this information would be needed to construct appropriate interventions. Additionally, this study was limited in its examination of behavioral and social factors found by other researchers to be associated with BMI trajectories. This study was limited in its examination of the relationship between SES, ethnicity, and sibling status in its 3-cluster and 4-cluster solution trajectories.

Conclusions

Our results add to the picture of BMI change patterns during the childhood growth period that precedes puberty. As suggested by Lane et al.,²⁵ understanding trajectories of weight gain may shed light on whether there are critical periods that put children at risk for changing BMI status. The body of research that has examined the trajectory of child overweight and obesity has clearly identified that obesity at school entry is a stable condition that is unlikely to change without intervention. Additionally, a pattern of psycho-social risk in the etiology of obesity has emerged that demonstrates clearer predictors of obesity risk among normal and overweight youngsters at school entry. These factors include family SES, race/ethnicity and immigrant status, maternal overweight during pregnancy, child birth weight, parent education, parenting style and maternal depression, and maternal smoking. Understanding the interplay of these risk factors on the developmental trajectories of overweight and obesity provides important guidance in directing efforts in child obesity prevention and intervention research. In sum, this work supports and extends prior obesity trajectory studies by focusing on an important growth period in middle childhood and provides a greater nuanced understanding of patterns that emerge during this period of child development.

IMPLICATIONS FOR SCHOOL HEALTH

Concerns about childhood obesity have resulted in an increase in studies focusing on both the prevalence of childhood obesity and an exploration of its various predictors.

Additionally, various health organizations, such as the American Pediatric Society and the Institute of Medicine, have promoted the central role of schools as a site for reducing overweight and obesity.^{43,44} School-based BMI screening, surveillance, and intervention programs are considered a potentially important part of a multifaceted strategy for reducing both child and adolescent overweight and obesity. A literature review and meta-analysis of child obesity interventions⁴⁵ supported these recommendations and found interventions implemented in schools could have a significant impact on weight and other outcomes. They found this especially heartening because children are exposed to many influences outside of the school setting as well as the complex nature of the causes of child overweight/obesity.

The pattern of stability within the obese trajectory group demonstrated in our study, especially for Hispanic and low SES children, clearly highlights the importance of the development and implementation of school based practices and programs that specifically target children in kindergarten and first grade and continue throughout the elementary school period. Interventions aimed at encouraging new, healthy behaviors are potentially likely to be effective when implemented during the key transition of entry into elementary school.

Some reviews^{46,47} generally suggest that, rather than single-component interventions, the most sustainable and beneficial approaches to obesity prevention involves multiple strategies that focus on the nutritional environment and policies of schools, enhanced physical education and physical activity during the school day (recess, before and after school programs classroom activity breaks) and home and community involvement. Specific school environment factors such as SES, geographic location (rural or urban), ethnic composition and social norms vary considerably across school districts and will require tailoring in different school environments. That said, there are some general categories of interventions, programs or policies that are worthy of consideration.

First, we suggest developing a BMI monitoring/surveillance program that focuses on aggregate data collection, not diagnosis, at schools. Where height and weight measurements are not included in annual health screenings the addition of these measures can provide schools with BMI tracking information and potentially serve to create an environment where healthy weight issues are discussed among staff, parents and local health organizations. Healthy weight information can impact not only the health of children, but also catalyze decisions to create and support environments that promote child health and influence societal priorities, resources, values and beliefs.⁴⁸

Second, we recommend implementing active and sustained multi-dimensional nutrition and physical activity programs that begin in kindergarten and continue through all elementary school grades. A cost-effectiveness analysis⁴⁹ found implementing an active PE policy at the elementary school level could influence physical activity levels in the population and potentially lead to reductions in BMI and obesity-related healthcare expenditures over 10 years. Finally, creating healthy food environments for children and including nutrition, culinary and gardening education have the potential for creating positive food preferences and dietary change especially when established early in life.

These child protective obesity recommendations and suggestions are made from the child's rights perspective⁵⁰ and are well grounded in an ethical, health equity framework. However, we recognize that given the current school economic climate, implementing and sustaining such programs can be difficult. Multi-component changes in school food service environments, health curriculum, and physical education also require related funding investments in schools. In the long term they also may necessitate restructuring school operations by increasing daily instructional hours, reconfiguring faculty expertise and team teaching arrangements, and the redesign of school facilities.

Our results have implications for schools, especially at the elementary level, in terms of developing improved strategies for identifying children at risk for overweight and obesity. The elementary school period of child growth is especially important because this age group may be more responsive to weight management interventions. Periodic measurement and comparison of BMI status over time can provide information to schools for developing programs aimed at at-risk elementary students to prevent them from moving to obesity. Results of this study support the suggestions of Lohrman et al¹⁹ that evaluations should be conducted at the elementary school level to comply with or initiate development of obesity prevention policies and program initiatives, as well as to determine which, if any, school-based initiatives are clearly associated with improved BMI trends, and therefore, might provide the greatest benefit. In addition, study results buttress the call of Balisteri and Cook¹⁶ for interventions that focus on preschool children's environments, especially for low SES Hispanic children.

Human Subjects Approval Statement

This study, as well as its procedures and measures, was approved by Oregon Research Institute's institutional review board—Assurance Identification #FWA00005934, IRB Registration #00000278.

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Figure 1.
State Distribution by 4-Cluster Solution

Note.

Each node gives the node size, a plot of the sequences in the node, and the discrepancy (s^2) within the node. The bottom of each parent node gives the retained split predictor together with its associated pseudo- R^2 . The global pseudo-F (8.05) indicates that the association of the sequences with terminal node membership is significant ($p < .001$), while the global pseudo- R^2 indicates that the proportion of the total discrepancy explained by the tree (.03) is significant ($p < .001$). The Levene statistic (3.61) indicates discrepancies of the nodes identified were heterogeneous ($p < .05$).

Figure 2.
Regression Tree Diagram

Table 1

Comparison of Existing BMI Trajectory Studies

Study	Sample	Methods	Trajectory Classes	Results
Balistreri KS, Van Hook J. Trajectories of overweight among US school children: A focus on social and economic characteristics. <i>Matern Child Health J</i> . 2011;15(5): 610-619.	14,000 U.S. kindergarten students taken from Early Childhood Longitudinal Study- Kindergarten Cohort (ECLS-K). Height/weight data were collected at K, at 1st, and once at a later date (3rd, 5th, or 8th).	Modeled prevalence of OW/OB from K to 8th using semiparametric mixture models. Developed grouping solution based on multiple models using 3 criteria (eg, BIC). Predicted membership using 20+ explanatory variables using multinomial logistics model.	Identified 3 trajectories: Normal (55%), Overweight (25%), Gradual Onset (20%).	Noted gender difference in group membership. SES, education, ethnicity, and immigrant status increased likelihood of being overweight/gradual onset.
Lane SP, Bluestone C, Burke CT. Trajectories of BMI from early childhood through early adolescence: SES and psychosocial predictors. <i>Br J Health Psychol</i> . 2013;18(1):66-82.	1,364 U.S. children birth to aged 11 years followed longitudinally in the NICHD Study of Early Child Care and Youth Development (SECCYD). Children, measured in person for height/weight, were from families enrolled from 10 communities, oversampled for minorities, single-parent HH, and <HS education. Non-English speaking families excluded.	Fit a Latent Growth Curve model within a latent class analysis, growth mixture model, to examine SES contribution to subtypes of BMI trajectories.	Identified 3 BMI membership (trajectory) classes: Stable (38.8%), Steady Increase (36.7%), and Elevated (24%).	Used trajectory classes to predict BMI category. For instance, 56% of <i>elevated</i> were OW at 6th grade, compared to 31% for <i>increased</i> , and 12% for <i>stable</i> . Reports evidence of both within and between class mediation of SES. Parenting styles and maternal depression mediated the impact of family income on patterns of BMI, but in differing degrees dependent on the class.
Li C, Goran MI, Kaur H, Nollen N, Ahluwalia JS. Developmental trajectories of overweight during childhood: role of early life factors. <i>Obesity</i> . 2007;15(3):760-771.	1,739 U.S. children ages 2 to 12 years born between 1984 through 1990. Data taken from NLSY79 survey of women and included 3 observations including in person height/weight measurement of children between 1986 to 2000.	Used latent growth mixture models (GMMs) on repeated measures of binary obesity (z-score > 95%) data by age.	Identified 3 classes: Early onset (10.9%), Late onset (5.2%), Never (83.9%).	Children in early or late onset groups were more likely to be male, black, higher birth weight, later birth order, and had mothers who smoked or had weight gain during pregnancy. Breastfeeding 4 months was associated with decreased risk of early and late onset obesity.
Magee CA, Caputi P, Iverson DC. Identification of distinct body mass index trajectories in Australian children. <i>Pediatr Obesity</i> . 2012;8:189-198.	4,601 Australian children from the Longitudinal Study of Australian Children ages 4-5 years at baseline were followed up at ages 6-7 years, 8-9 years, and 10-11 years with height/weight measures.	Used Growth Mixture Modelling.	Four distinct trajectories were identified: (i) High Risk Overweight, (ii) Early Onset Overweight, (iii) Later Onset Overweight, and (iv) Healthy Weight.	Raw body mass index values were more sensitive to changes in body composition than BMI categories. Mother overweight, education, smoking, and child birth weight were significant predictors of BMI risk trajectories.
Pryor LE, Tremblay RE, Boivin M, et al. Developmental trajectories of body mass index in early childhood and their risk factors: an 8-year longitudinal study. <i>Arch Pediatr Adolesc Med</i> . 2011;165(10): 906-912.	Canadian children selected through birth registries for the Quebec Longitudinal Study of Child Development were followed from 5 months to 8 years old. Height/weight measures were derived from 5 months thru 5 years of age via caregiver report. At ages 6, 7, and 8 years anthropometric measurements were obtained by a trained interviewer.	Semiparametric modeling method from raw BMI values at each age.	Three trajectories of BMI were identified: low stable (54.5%), moderate (41%), high-rising (4.5%).	Maternal overweight and maternal smoking during pregnancy were associated with the high-rising group.

Table 2

Baseline Values for Variables and Cases Used in the Sequence Analysis

Description	N	%
BMI category		
1 = underweight	5	1
2 = normal	278	67
3 = overweight	63	15
4 = obese	68	16
Sex		
1 = male	205	50
2 = female	209	50
Qualifies for subsidized meals		
1 = no	281	68
2 = yes	133	32
Number of siblings in house		
1 = none	219	53
2 = one or more	195	47
Grade at first observation		
0 = kindergarten	200	48
1 = first grade	214	52
Race/Ethnicity		
1 = White	314	76
2 = Hispanic	62	15
3 = Other	38	9

Table 3

Transition Probabilities for Combined, 3-trajectory and 4-trajectory Cluster Solutions

Combined (N = 414)				
	-> u	-> n	-> ow	-> ob
u ->	0.39	0.61	0.00	0.00
n ->	0.01	0.92	0.06	0.01
ow ->	0.00	0.16	0.60	0.24
ob ->	0.00	0.03	0.10	0.87
Normal (N = 264)^{3/4}				
	-> u	-> n	-> ow	-> ob
u ->	0.39	0.61	0.00	0.00
n ->	0.01	0.96	0.03	0.00
ow ->	0.00	0.65	0.30	0.04
ob ->	0.00	1.00	0.00	0.00
Mixed (N = 60)^{3/4}				
	-> u	-> n	-> ow	-> ob
u ->	0.00	0.00	0.00	0.00
n ->	0.00	0.41	0.56	0.03
ow ->	0.00	0.15	0.74	0.11
ob ->	0.00	0.07	0.93	0.00
Stepped-3 (N = 90)³				
	-> u	-> n	-> ow	-> ob
u ->	0.00	0.00	0.00	0.00
n ->	0.00	0.22	0.56	0.22
ow ->	0.00	0.00	0.34	0.66
ob ->	0.00	0.02	0.06	0.93
Stepped-4 (N = 38)⁴				
	-> u	-> n	-> ow	-> ob
u ->	0.00	0.00	0.00	0.00
n ->	0.00	0.22	0.56	0.22
ow ->	0.00	0.00	0.34	0.66
ob ->	0.00	0.02	0.22	0.75
Obese (N = 52)⁴				
	-> u	-> n	-> ow	-> ob
u ->	0.00	0.00	0.00	0.00
n ->	0.00	0.00	0.00	0.00

Obese (N = 52) ⁴				
	-> u	-> n	-> ow	-> ob
ow ->	0.00	0.00	0.00	0.00
ob ->	0.00	0.00	0.00	1.00

Note. Bold values in Stepped-3 cluster represent the combined transition probabilities shown in Stepped-4 and Obese clusters. u = underweight; n = normal; ow = overweight; ob = obese.

^{3/4} Transition probabilities associated with both 3-cluster and 4 cluster solutions.

³ Transition probabilities associated with only 3-cluster solution.

⁴ Transition probabilities associated with only 4-cluster solution.