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Authors
Konty, Kevin J
Day, Sophia E
Napier, Melanie D
et al.

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Context, importance, and process for creating a body mass index surveillance system to monitor childhood obesity within the New York City public school setting

Kevin J. Konty [a], Sophia E. Day [a,b], Melanie D. Napier [c], Erica Irvin [d], Hannah R. Thompson [e], Emily M. D'Agostino [f,g,*]

[a] *Office of School Health, Research and Analytics, New York City Department of Health and Mental Hygiene, New York, NY USA*
[b] *Department of Epidemiology and Biostatistics, City University of New York School of Public Health, New York, NY USA*
[c] *Department of Epidemiology, University of North Carolina at Chapel Hill, Chapel Hill, NC USA*
[d] *Office of School Wellness Programs, New York City Department of Education, New York, NY USA*
[e] *Department of Community Health Science, School of Public Health, University of California Berkley, Berkley, CA USA*
[f] *Department of Orthopaedic Surgery, Duke University School of Medicine, Durham, NC USA*
[g] *Department of Population Health Sciences, Duke University School of Medicine, Durham, NC USA*

A B S T R A C T

The Office of School Health, a joint program of the Departments of Health and Education, administers New York City's (NYC) body mass index (BMI) surveillance system to monitor childhood obesity. We describe the context, importance, and process for creating a multi-agency, school-based BMI surveillance system using BMI collected from annual FITNESSGRAM® physical fitness assessments conducted as part of a larger physical activity and wellness curriculum in NYC public schools. We also summarize our current system and methodology, highlighting the types of data and data sources that comprise the system and partnership between the Departments of Health and Education that enable data sharing. Strategies for addressing threats to data quality, including missing data, biologically implausible values, and imprecise/subjective weight or height equipment are discussed. We also review current and future surveillance data products, and provide recommendations for collecting, analyzing, interpreting, and reporting BMI data for childhood obesity surveillance. Collaboration between Departments of Health and Education as well as attention to safeguards of BMI reporting and data quality threats have enabled NYC to collect high quality BMI data to accurately monitor childhood obesity trends. These findings have implications for youth BMI surveillance systems in the United States and globally.

1. Background

1.1. New York City's childhood obesity surveillance system

Obesity among children and youth has become one of the most critical public health problems in the past four decades in the US. (Sanyaolu et al., 2019) Between 1980 and 2016, obesity prevalence has more than doubled among children aged 6–11, from 7% to approximately 19%, and quadrupled among youth aged 12–19, from 5% to approximately 21%. (Ogden et al., 2014; Hales et al., 2017) To address this ongoing epidemic, school-based obesity surveillance and screening programs have been proposed or mandated in up to 29 states. (Ruggieri and Bass, 2015) The Office of School Health (OSH), a joint program of the Departments of Health and Mental Hygiene (DOH) and Education (DOE), administers New York City's (NYC) childhood obesity surveillance system. The OSH provides health and preventive services to students (https://www.schools.nyc.gov/school-life/health-and-wellness/health-services). Within the OSH, the DOH's Data Science and Research team and DOE's Office of School Wellness Programs (OSWP) partner to collect, analyze, monitor, and disseminate the prevalence of and trends in obesity and physical fitness among NYC children and adolescents. In this partnership, the DOE provides the Data Science and Research team with student-level demographic, enrollment, absenteeism, home address, socioeconomic status (e.g. participation in reduced price/free lunch programs), academic outcomes, fitness and height and weight measurements and dates from the FITNESSGRAM® assessment as well as school-level information such as school address, staffing, start times, and facility information. In exchange, the DOH performs population-level data analysis, monitoring, and reporting of body mass index (BMI) and physical fitness among the student population; assesses the quality of DOE-provided data; and provides data-based feedback to OSWP to improve DOE data collection, database design, and

* Corresponding author at: Department of Orthopaedic Surgery, Duke University School of Medicine, Durham, NC USA.
E-mail address: emily.m.dagostino@duke.edu (E. M. D'Agostino).

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program planning and evaluation of interventions to promote student health and well-being.

1.2. Public health significance

Schools are logical settings in which to focus youth obesity prevention efforts; no other setting has as much intensive, continuous contact (≥six hours/day for 180 days/year) with school-age children. (Story et al., 2006) The 2005 landmark report *'Preventing Childhood Obesity: Health in the Balance'* recommended annual school-based BMI surveillance programs as a way to monitor and address the growing childhood obesity epidemic. (Schwimmer, 2005) Since then, an additional Institute of Medicine (IOM) report, (Committee on Accelerating Progress in Obesity Prevention, 2012) the American Public Health Association, (APHA, 2002) and the American Heart Association (AHA) have also supported school-based BMI surveillance (See Table 1) (AHA, 2008).

Surveillance systems are defined as ongoing and systematic data collection, analysis, and interpretation to describe and monitor health events (CDC, 1988). Routinely collected health data can also support the rapid advancement in public health professionals' ability to detect and respond to a wide range of chronic health conditions such as diabetes, hypertension, and high cholesterol, monitor active drug safety and smoking behavior, and evaluate suicide risk. (Thorpe, 2017) For example, US school-based prevalence of healthy behaviors, obesity, and asthma are monitored through the Youth Risk Behavior Surveillance System using annual self-reported data administered by the Centers for Disease Control and Prevention. (Kann, 2017) Similarly, US population-level health and nutritional status of both youth and adults are monitored by the National Health and Nutrition Examination Survey based on annual survey sampling using interviews and physical examinations. (Centers for Disease Control and Prevention, 2020) Surveillance tools also can be used to evaluate youth health intervention effectiveness, and can be used to support pediatricians and other healthcare providers in initiating conversations with parents and their children about improving nutrition and physical activity habits. Important attributes of surveillance systems include simplicity, flexibility, acceptability, predictive value, representativeness, timeliness, usefulness and cost (CDC, 1988).

Well-designed and implemented school-based BMI prevention programs have been shown to effectively promote physical activity and healthy eating, (Sobol-Goldberg et al., 2013; Lavelle et al., 2012; Kothandan, 2014; Katz, 2009; Gonzalez-Suarez et al., 2009) and improve high cholesterol. (Dobbins et al., 2013; Harris et al., 2009; Williams et al., 2013) However, school-based programs have not shown a positive effect for other health metrics such as BMI and blood pressure for reasons that are unclear, but may include insufficient "quantity" of physical activity interventions to improve BMI. Routine youth physical activity (PA) supports healthy habits early in life, with lasting benefits into adulthood, including protection against obesity, high blood pressure, and depression, elevated insulin and blood lipids. (U.S. Department of Health and Human Services, 2018) From a public health perspective, these beneficial effects warrant continued investment in these programs.

Jurisdictions that have established BMI surveillance and screening programs are heavily influenced by federal guidelines, and so are incentivized to use a common set of metrics necessary to track BMI for individual students throughout and across school years. However, prior reports from data in school-based settings (California Department of Education, 2020; Georgia Department of Education, 2017; Texas Education Agency, 2020) include just aggregate (school or grade) level findings, do not consider changes in testing reporting standards or bias due to voluntary school reporting of data, and do not report annual changes in individual children's BMI. NY State in fact reports just the percentage of children with obesity for pre-K, K, 2nd, 4th, 7th, and 10th grade students. In contrast, metrics available in the NYC FITNESSGRAM®, such as annual individul-level BMI and sociodemographic records, allow school and public health officials to get a more complete picture of the obesity epidemic in their jurisdictions. It is also important to build BMI surveillance systems that are equipped to leverage input from widely-available, administrative data sources. The insights we can glean from them can support better evaluation, program, and policy targeting.

The objectives of this paper are to describe the process of creating and maintaining an annual BMI surveillance system to monitor childhood obesity in NYC public school children using population-level data available from the NYC DOH and DOE and the FITNESSGRAM® assessment.

Table 1
Body Mass Index (BMI).

BMI is a common measure of weight adjusted for height: $\frac{\text{Weight(kg)}}{\{\text{Height(m)}\}^2} = \frac{\text{Weight(lb)} \times 703}{\{\text{Height(in)}\}^2}$
While BMI does not measure body fat directly, it is an inexpensive and easy method of screening for potential obesity-related health risks and surveillance of population-level childhood obesity. BMI has been correlated with direct measures of body fat, including skinfold thickness and dual x-ray absorptiometry. (Kelly et al., 2013; Little and Rubin, 2002) Thus, using BMI to define obesity has several advantages over other more invasive, if precise, metrics.
BMI categories for adults are fixed, but for children aged 2 through 19 years, BMI is expressed using percentiles that take into account factors such as age-in-months, sex, growth, and level of secondary sexual maturation, that affect the relationship between BMI and body fat among children. In the US, percentiles specific to age and sex are calculated from CDC growth charts (Plowman and Meredith, 2013) which compare a given BMI to the BMI values of other US children of the same sex and age that were surveyed from national data collected from 1963 to 65 to 1988–94. As defined by the CDC, a child's weight status can be underweight (BMI-for-age $<$ 5th percentile), healthy weight (BMI-for-age $\geq$ 5th and $<$ 85th percentile), overweight (BMI-for-age $\geq$ 85th and $<$ 95th percentile); obese (BMI-for-age $\geq$ 95th percentile); and severely (or extremely) obese (BMI-for-age $\geq$ 120% of the 95th percentile). (Langkamp et al., 2010; Bezold et al., 2014) The definition for severe (or extreme) obesity has been recommended by the American Heart Association (AHA) as a flexible means by which to evaluate heavier youth (CDC. A SAS Program for the, 2000) and is approximately equal to the empirical 99th percentile in the CDC growth charts. (California Department of Education. Physical Fitness Test Results (CA Dept of Education). Accessed July 8, 2020)

2. Methods

2.1. Data source

The NYC childhood obesity surveillance system consists of gathering data from disparate sources (DOE administrative databases, the American Community Survey (ACS), the US Census, and NYC FITNESSGRAM® assessments) into one comprehensive record for each student for each year of attendance in public school. This longitudinal, student-level analytic dataset is used to define the NYC public school student population to construct prevalence and trend estimates for BMI surveillance and fitness outcomes. Trends in BMI prevalence have been examined annually for approximately 860,000 public school students per year in all grades (K-12) since 2006/07. Separating the surveillance system into two components—the student population data and student health outcome information—enables this process to be efficient and consistent in investigating multiple health outcomes related to obesity across the same student population.

2.1.1. Administrative databases

Since 2011/12, the DOE has provided daily enrollment records for each student for all school years. Caregiver/custodian report of child demographic information includes name, sex, race/ethnicity, date of birth, home language, place of birth, home address, and eligibility for free or reduced-price meals. Student enrollment records include student grade level, days absent and present, disability status, English Language Learner status, and academic and graduation outcomes as well as the classroom, school, and school address where the student is enrolled.

2.1.2. Geographical databases

In addition to student-level information, home and school neighborhood-level characteristics are also incorporated into the longitudinal analytic dataset, drawing from the ACS and the US Census. To link to ACS/Census neighborhood characteristics, we construct neighborhood variables by first geocoding students' school and home addresses from enrollment files to obtain school and home X and Y coordinates for each student record in each school year. We next use these X and Y coordinates overlaid with neighborhood boundary shape files to define school and home neighborhoods for various NYC geographies (i.e. Census tracts, zip codes, etc.). (Day et al., 2016) When geocoded coordinates are unavailable due to missing home address, we impute the address as recorded for the same student in another school year closest in time to the school year missing an address. The percentage of students whose address is not able to be imputed is low (Table 2).

An important neighborhood-level variable used for both the student home and the school location constructed from ACS/Census data is the NYC Area-Based Poverty Measure, which indicates the percent of the population residing in an area (i.e. zip code, Census tract) that live below the federal poverty threshold. (Toprani and Hadler, 2013) This measure was constructed from the Census until 2010, and then from pooling the most recent five years of data from the ACS. The DOH has adopted this measure as a standard indicator of neighborhood-level socioeconomic status (SES) because it allows for consistency in reporting SES-related findings across time and jurisdictions. We also include in the longitudinal analytic dataset whether a school or home is located within areas that have DOH Neighborhood Health Action Centers (NHAC), previously referred to as District Public Health Offices. These local offices coordinate health services, social services, and community programs under one roof to target resources, programs, and attention to areas of the city defined by low income and disproportionally high rates of morbidity and mortality. (Neighborhood Health Action Centers, 2019).

2.1.3. FITNESSGRAM® database

The NYC FITNESSGRAM® contributes both student population data and health data to the BMI surveillance system. The DOE's OSWP oversees NYC FITNESSGRAM®, an annual physical fitness assessment and reporting program for youth developed by The Cooper Institute of Aerobic Research in 1982 (Plowman and Meredith, 2013) and widely used in the US. FITNESSGRAM® includes a set of six tests that measure components of health-related fitness: body composition (BMI, skin folds or bioelectrical impedance), muscular strength and muscular endurance (push-up and curl-up tests), flexibility (sit and reach test), and aerobic capacity (PACER test (Progressive Aerobic Cardiovascular Endurance Run). An additional test, the trunk lift, is a measure of lower back strength and flexibility). Each test is evaluated using a set of age- and sex-specific standards that reference a relevant set of health criteria. For example, body composition/BMI standards were established based on data from the nationally representative NHANES dataset that showed levels of body fatness and BMI associated with increased risk of metabolic syndrome. (Laurson et al., 2011) Thus, student progress on the FITNESSGRAM® can be a proxy for health status, as obesity is predictive of current and future health outcomes.

Since 2006, physical education teachers have administered the NYC FITNESSGRAM® for all students in grades K-12 once each year between September and May in conjunction with the DOE-recommended "Physical Best" curriculum that teaches principles for healthy living along with physical fitness instruction. Since then, it has become an integral part of NYC's physical fitness and obesity prevention initiatives. For each student, the date of measurement, person entering the data, and student birth date, sex, height, and weight measurements are recorded and converted to BMI percentiles using the Centers for Disease Control and Prevention (CDC) 2000 growth charts (CDC, 2000). The OSWP is responsible for providing reports of the yearly NYC FITNESSGRAM® assessments to parents and students (see Supplemental Figure 1). The reports compare each child's fitness scores with a set of FITNESSGRAM® standards for physical fitness ("Healthy Fitness Zones" (HFZ), described in the "Data Analysis" section), that are defined empirically from the National Health and Nutrition Examination Survey. An important component of the report is that rather than comparing each student to a national or school average, students are compared against themselves. Also, reports present weight status in combination with other fitness tests to help youth to pursue personal fitness goals for lifelong health to reduce risk of weight dissatisfaction and other adverse outcomes that are associated with BMI screening and reporting alone. In addition, school resources (e.g. specialty recreation classes and coordinators) for healthy weight and fitness promotion are offered to families and schools through the OWSP School Wellness Programs portal (NYC Department of Education, 2021).

In the 2006/07 school year, the first year of available data, 47% of K-12 and 62% of K-8 students had a complete FITNESSGRAM® body composition assessment. Two years later in 2008/09, the percentage was up to 80% and 89%, respectively, and has remained consistently high since then. By 2016/17, the latest year of analyzed data, 91% of K-12 and 94% of K-8 public school students had a complete assessment (Table 3). As of this publication, the database contains over 8.7 million BMI measurements for nearly three million unique public school students. More information on NYC FITNESSGRAM® can be found at https://www.schools.nyc.gov/school-life/learning/subjects/physical-education.

2.2. Defining student population and BMI

To produce BMI prevalence estimates and trends, the NYC student

Table 2
Percentage of students whose home address is unable to be imputed[a] for 2006/07 through 2016/17.

School Year	Percentage in Grades (%)	
	K-12	K-8
2006/07	24.2	30.6
2007/08	16.6	21.1
2008/09	8.6	9.9
2009/10	5.9	6.4
2010/11	4.3	4.7
2011/12	1.4	1.5
2012/13	0.5	0.5
2013/14	0.4	0.5
2014/15	0.4	0.5
2015/16	0.5	0.5
2016/17	0.5	0.6

[a] Students with either no other records with location information or with an address record from another school and school year more than two years away from the current school year.

Table 3
Percentage of students with valid BMI measurements for 2006/07 through 2016/17.

School Year	Percentage in Grades (%)	
	K-12	K-8
2006/07	47	62
2007/08	66	77
2008/09	80	89
2009/10	85	93
2010/11	87	94
2011/12	89	95
2012/13	89	94
2013/14	91	95
2014/15	91	94
2015/16	91	95
2016/17	91	94

population is limited to public school students enrolled in grades K-8 (ages 5 < 16), in non-alternative (i.e. non-charter) and non-special education school districts as of October 31st of that school year ("Official" enrollment) without biologically implausible values (BIVs) for anthropometric measures defined according to CDC's BMI percentile-for-sex and age cut-points. (CDC, 2000) This "Official" enrollment definition maximizes the accuracy and diversity of the NYC student population by including students who dropped out of school in the middle or end of the school year (mostly seen among high school students), and also excluding students who were enrolled at the beginning of the school year, but never attended school or switched to a non-public school before the end of the first month of the school year.

With each new school year of data, the student population is defined for that year and redefined for all previous school years using the new school year of data to improve student records from the previous school years (e.g., update fields with previously missing values). Just as the student population is updated each school year, prevalence estimates of underweight, healthy weight, overweight, obese, and severely obese are calculated using the updated student population data for all school years (i.e., prevalence estimates are calculated for the current school year and recalculated for the previous school years). Therefore, the release of any new years' BMI trend data would have slightly improved estimates for all previous years. For each school year, we weight the student records with measured BMI to be representative of the enrollment population using an iterative raking process that follows procedures similar to those for nonresponse adjustments (or post-stratification) in surveys. (Battaglia et al., 2013) The raking process uses race/ethnicity, school borough by NHAC neighborhood (e.g. Brooklyn-NHAC), participation in reduced price/free lunch programs (i.e. meal code status), grade, sex, age, and grade type (K-5 vs. 6–8) as population marginal control totals (*see section below*). However, our large sample size allows for additional adjustment variables. Prevalence estimates for 2006/07 through 2010/11 were created using these weights and accounted for clustering by school. Estimates were published in a 2011 MMWR (Berger et al., 2011) and in a 2014 Preventing Chronic Disease article (Day et al., 2014) After switching to an "Official" enrollment definition for 2011/12, our previous 2006/07 through 2010/11 estimates were revised.

To examine obesity trends each year, a binary logit model for each of the six BMI categories (i.e., underweight, healthy weight, overweight, obese, and severely obese) is built wherein the probability of being in a given category is modeled on time (an integer value that increases from 0 to 4 corresponding to the 2006/07 to 2010/11 school years and, separately, from 0 to 5 corresponding to the 2011/12 to 2016/17 school years). The models are clustered at the school- and student-level, weighted to be representative of the student enrollment for each school year (i.e., both students with and without complete BMI measurements for the given school year), and control for student age, sex, race/ethnicity, language spoken at home, place of birth, and the school borough by NHAC neighborhood status, as well as the three way interaction of age in months by sex and by race/ethnicity. Separate analyses are typically run for subgroups (i.e. by sex, by race/ethnicity) as well as for each of time periods (e.g., 2006/07 to 2010/11 and 2011/12 to 2016/17). Additional obesity trends also can be examined by processing the data using z-scores and World Health Organization cutoffs for weight categories (Onis et al., 2007) and BIVs (Freedman et al., 2015) to facilitate international comparisons.

2.3. Data quality

Both student population and BMI information come from large administrative databases maintained and collected for other purposes. Although a number of challenges have been identified with use of such data, (Hand, 2018) several factors contribute to the strength of our dataset. Foremost is the broad scope of data collection which allow for centralized establishment of data quality standards, such as reporting requirements or the use of standardized scales. Other challenges discussed in the next section include handling of missing data and BIVs, high response rate, objective weight and height measurements, and the continual refinement of prior year BMI trend estimates that occurs with each annual update.

3. Results

3.1. Interpretation Issues: Considerations for ensuring anthropometric data quality

3.1.1. DOH-DOE partnership

By partnering with DOE, the DOH childhood obesity prevention program can leverage the same data points that the DOE is required to collect, often from primary sources (i.e. caregivers/custodians), and with supporting documentation. The benefits of this alliance are tremendous. Many of the DOE-provided variables (e.g. age, race/ethnicity, sex, grade, absenteeism, attendance) are needed to identify the student, calculate BMI percentile, and/or define the student population, all of which are critical for accurately calculating population-level trends. The use of educational administrative databases has the advantage of providing a rich, longitudinal source of data on each student and a potentially efficient use of limited resources. In this case, DOH worked with DOE over several years to gain access to daily attendance records for each student, which allowed us to refine our student population definition from "Active" enrollment (less precise) to "Official" enrollment (more precise) to capture students who dropped out or transferred. The inclusion of these students led to a BMI prevalence that more accurately reflected the NYC public school population. Data collection is approved by the DOH Institutional Review Board (Protocol # 14–019) and is determined by that board to be public health surveillance that is not research and therefore exempt from the requirement for obtaining written informed consent. Students who do not want to participate in an activity, or caregivers who do not want their children to participate in an activity, are able to opt out of participation in the activity through their schools. This study represents a description of the methods, characteristics and data used in a surveillance system.

3.1.2. Objective weight and height measurements

Accurate and reliable data collection is the foundation of a strong surveillance system. This partnership has involved investing in training teachers, nurses, and administrators on proper techniques for measuring height and weight. Specifically, NYC physical education staff receive formal training on testing protocols to enhance consistency across administrators, such as with testing manuals, video-based training, site-visits, and use of calibrated scales. (Plowman and Meredith, 2013) Teachers can enter data into the NYC FITNESSGRAM® app only after having attended several trainings, including PE Basics I: Lesson Planning to Incorporate Fitness and Assessment.

This partnership also has involved investing in standardized, reliable, calibrated equipment. For example, in the 2011/12 school year, new self-calibrating, digital scales that included stadiometers were purchased and installed in 1,500 schools as part of the CDC Communities Putting Prevention to Work grants. In that first year, 77% of children were measured using the new scales, and we observed an increase in the prevalence of obesity among K-8 students to 21.5%, up from 21.2% the previous school year following several years of decreasing rates. Because of measurement error associated with the previously-used scales, there could have been school-level or scale-level effects that affected the interpretation of BMI trends. To determine whether the new scales accounted for all or some of the increase in obesity observed, age- and sex-specific percentiles, z-scores, and Biologically Implausible Values (BIVs) were created using CDC growth charts (obesity defined as BMI $\geq$ 95th percentile) based on annual height and weight measurements collected for all NYC public school children 2006–2011. A repeated cross-sectional trend model was used to quantify the impact of the new scales while controlling for demographic characteristics. Additionally, we identified 3 non-mutually exclusive mechanisms by which the new scales may have impacted obesity estimates: improved height measurements, reduction in BIVs, and reduction in entries ending in 0 or 5, indicating rounding. For students in grades K-8, approximately 10% of the increase in obesity could be attributed to a reduction in the number of BIVs in height, weight, or BMI; 75% of the increase could be attributed to a reduction in shrinking heights from year to year; and 15% was due to being measured on a new scale versus not being measured on a new scale. For all of these reasons, obesity estimates from 2011/12 onwards are not comparable to estimates from 2006/07 through 2010/11 since the impact of introducing these standardized scales differs by grade, sex, poverty, and school-level characteristics, which are predictors of student BMI. At the same time, OSWP provided support to teachers who needed re-training. Other states, like Arkansas, designed their own stadiometers and had them built by the Arkansas Department of Corrections to meet their needs while the Arkansas Center for Health Improvement refined a "train-the-trainer" model to educate school nurses on a standardized measurement protocol. (Thompson and Card-Higginson, 2009) While specific details may vary from system to system, attention to rigorous data collection practices support quality data.

3.1.3. *Missing and biologically implausible BMI values*

To identify outlier measurements or biologically implausible values for height, weight, weight-for-height, and BMI, we use output BIV flags calculated from the modified z-scores in the macro for the 2000 CDC age- and sex-specific growth charts. (CDC, 2000); (Kuczmarski et al., 2000) The z-scores define which values are beyond the range of what one would normally expect to find in a population. The upper BIV cut-points for weight, height, and BMI were increased in 2016 to address the limitation of the previous cut-points, (Freedman et al., 2015) which erroneously identified children as having implausible values when they were, in fact, severely obese. (Day et al., 2014; Kelly et al., 2013) As a result of using the new BIV cut-points to define extreme values, NYC's obesity estimates slightly increased, similar to the effects reported for NHANES. (Freedman et al., 2015)

Missing data is a common challenge in analyzing longitudinal data whose mishandling can lead to bias in unexpected ways, especially when removing cases with missing data in a non-representative sample. (Little and Rubin, 2002; Langkamp et al., 2010) Thus, eliminating cases with missing data, particularly $>$ 10% missing, is often not the best option. Currently, we handle missing data by weighting the student records with measured BMI to be representative of the enrollment population using the iterative raking process described above. (Battaglia et al., 2013) In the future, we hope to leverage the longitudinal structure of the data (i.e. multiple years of information on a particular student) to impute missing information. (Little and Rubin, 2002) This would be accomplished by drawing from height and weight measurements and sociodemographic variables (e.g., race/ethnicity, gender, place of birth, grade level, free/reduced meal status, home language, and school attendance) from youth in the same schools by age group, sex and over time in order to pool observations across students and years of data collection. Using a multinomial logit model, we would predict the probability for each student with non-measured BMI, for example, of being underweight, healthy weight, overweight, obese, and severely obese, using the same covariates that were used as marginal controls, with the greatest predictor being the previous year's BMI.

In addition to student-level longitudinal flags, we also plan to implement school-level flags that are both cross-sectional and longitudinal, to capture implausible values that can't be captured on an individual level. Cross-sectional flags may include school and teacher checks for a high proportion of measurements identified as being BIV for height, weight, BMI, or weight-for-height, shrinking, too low/high BMI z-score change, or with a high percentage of measurements rounded to zero or five. Longitudinal flags may include checks for percentage of students flagged for invalid BMI z-score change from previous year. Such flags have already been used to identify schools that have had systematic problems or poor-quality data related to BMI values, resulting in additional training for teachers on how to measure and enter FITNESSGRAM® data provided by OSWP.

3.2. *Linkage to other databases*

Because the surveillance system consists of two components (individual students and schools), it is quite flexible and able to be linked to other databases to examine other outcomes of interest. Pairing NYC student population information with student health information from additional sources permits investigation of the relationships between students, school metrics, and health outcomes. In NYC, FITNESSGRAM® assessment data can be combined with student population information for surveillance of physical fitness as an outcome in addition to BMI. For surveillance of diabetes, asthma, vision compliance, and other conditions, the Automated Student Health Record (a web-based electronic health record that records all student visits to the school nurse for illness, injury, or preauthorized treatment) can be used. At the end of each school day, the daily school nurse/medical room visit data in this health record is automatically uploaded to a database at DOH so that daily syndromic surveillance can be performed to detect events that might indicate potential outbreaks of illness. Data that are recorded include the date and time of the school nurse visit, student age, sex, school ID, grade, classroom, medication information, residential zip code, and a reason for their nurse visit chosen from a predefined list. The system is also flexible enough to evaluate interventions at the school or community level. Several papers have already reported data from the BMI surveillance system presenting findings on the relationships between fitness and academics, (Bezold et al., 2014) the built environment, (Bezold et al., 2017) and absenteeism. (D'Agostino et al., 2018; D'Agostino et al., 2018) BMI trend data is also used to report on the percentage of chronic absenteeism among NYC elementary school students' by residential neighborhood as part of the DOH's Community Health Profiles (http://www1.nyc.gov/site/doh/data/data-publications/profiles.page). These data linkages are permitted through memorandums of understanding between the NYC DOH and other NYC and NY state agencies.

3.3. *Data release and accessibility*

The NYC FITNESSGRAM® Trendbook for BMI that describes obesity trends overall and by several important sociodemographic metrics for students in grades K-8 has been updated each year since 2006/07. While not available publicly, the Trendbook is shared across NYC DOH for dissemination with community partners. This Trendbook includes detailed estimates for all scales to support local patterns in youth obesity from 2006 /07 by age group, gender, grade level, place of birth, home language and borough at different geographics (borough, district, and zip code). Additional information can be requested via a data request from the authors. In the future, a summary infographic of obesity prevalence estimates and detailed tables can also be requested by emailing the authors. The DOH processes all data requests and shares it with the DOE so that everyone uses the same standardized clean data. There are currently no plans to publicly release student-level data; however, interested parties can submit a data request to the DOE Research and Policy Support Group. Instructions for completing a data request can be found at: http://schools.nyc.gov/Accountability/data/DataRequests.

4. Discussion

As obesity-related diseases continue to burden the US health care system, state- and metropolitan-level BMI data are essential to effectively confronting childhood obesity. As of 2014, NY is one of 25 states

(4 additional pending) that has mandated BMI assessments for public school children: (Ruggieri and Bass, 2015; SHAPE America, 2016; Linchey and Madsen, 2011) Even states without requirements to monitor youth BMI in school-based settings have been reported to do so voluntarily. (Linchey and Madsen, 2011) Thus for many settings, school-based BMI surveillance and screening programs will provide the local estimates that are urgently needed to evaluate prevention programs, assess progress, and understand disparities. School-based BMI surveillance systems also minimize costs associated with creating a new surveillance program, while providing timely information that can drive public health action, consider changing technologies, health care systems, and include relevant stakeholders to promote public health efficiency, effectiveness, and rigor. (Public Health Surveillance Systems, 2017). Collaboration between Departments of Health and Education as well as attention to data quality threats has enabled NYC to collect high quality BMI data to accurately monitor childhood obesity trends. These findings have implications for youth BMI surveillance systems in the US and globally.

4.1. Strengths and limitations

The NYC FITNESSGRAM® surveillance system draws from individual NYC student-level data collected annually at every grade level, which permits prospective tracking of shifts in youth physical fitness on a population scale. Youth obesity surveillance in NYC supports a comprehensive approach to curb obesity by the NYC DOH and DOE through school-based interventions and policy initiatives. (Sacks et al., 2015; Perlman et al., 2012; Nonas et al., 2014; Dunn et al., 2012; NYC, 2019) These measures include reducing consumption of sugar sweetened beverages, increasing fruit and vegetable consumption, in-class fitness breaks, and out-of-school physical activity programs. Moreover, prior research findings derived from the NYC FITNESSGRAM® reinforce the importance of monitoring youth obesity to demonstrate persistent disparities, (Day et al., 2020) and inform renewed thinking regarding the design and implementation of effective interventions.

Although the NYC FITNESSGRAM® can serve as a population-level surveillance tool, findings are limited to eligible participants. Students from schools that are not mandated to participate in the FITNESSGRAM® (private, charter, and special education schools; approximately 18%, 10%, and 2% of elementary, middle and high school children in each school year, respectively) are not included. In addition, variation across FITNESSGRAM® testing sites and test administrators may result in random measurement error and systematic bias.

As BMI measurement policies become more widespread, obesity prevention advocates can garner critical information from existing school-based surveillance and screening efforts around the nation, including methods for ensuring good data quality. It is particularly important for school-based BMI programs to share knowledge and resources to ensure that accurate information is used to produce estimates given there are no standard guidelines for data collection and analysis. However, the methods used for youth obesity surveillance in other settings are difficult to find in the literature. It is possible, though not likely, that states, and metropolitan centers in particular, are approaching data quality in the same way. Thus, this paper documents our approach and rationale for the NYC school-based youth obesity surveillance system (surveilling the largest school district in the nation), and provides lessons learned while highlighting how we address common quality pitfalls that could undermine the integrity of BMI prevalence estimates. Our hope is that by doing so we can continue the conversation with other states implementing their own school-based BMI systems nationally, (Quirk and Rapporteurs, 2015) and together put forth the best possible data to inform the prevention of youth obesity.

5. Disclosures

Melanie D. Napier, Hannah R. Thompson, and Emily M. D'Agostino are paid consultants for the New York City Department of Health and Mental Hygiene. The authors do not have any other possible, perceived, or real financial conflicts of interest or partnership with commercial interests to declare.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pmedr.2022.101704.

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