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Linking electronic health records with community-level data to understand childhood obesity risk

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Summary

Background—Environmental and socioeconomic factors should be considered along with individual characteristics when determining risk for childhood obesity.

Objective—To assess relationships and interactions among economic hardship index and race/ethnicity, age, and sex in regards to childhood obesity rates in Wisconsin children using an electronic health record dataset.

Methods—Data were collected using the University of Wisconsin Public Health Information Exchange (PHINEX) database, which links electronic health records with census-derived community-level data. Records from 53,775 children seen at UW clinics from 2007–2012 were included. Mixed effects modeling was used to determine obesity rates and the interaction of EHI with covariates (race/ethnicity, age, sex). When significant interactions were determined, linear regression analyses were performed for each subgroup (e.g., by age groups).

Results—The overall obesity rate was 11.7%, and significant racial/ethnic disparities were detected. Childhood obesity was significantly associated with EHI at the community level (r=0.62, $p<0.0001$). A significant interaction was determined between EHI and both race/ethnicity and age on obesity rates.

Conclusions—Reducing economic disparities and improving environmental conditions may influence childhood obesity risk in some, but not all, races and ethnicities. Furthermore, the

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Conflict of Interest Statement

The authors have no conflicts of interest to report.

Author Contributions

ET developed the study design, interpreted data, conducted the literature search, and prepared the manuscript. TF assisted with data interpretation and manuscript writing. AT performed the data collection, analysis, and interpretation. LH contributed to study design, data collection and interpretation, and manuscript writing.

impact of EHI on obesity may be compounded over time. Our findings demonstrate the utility of linking electronic health information with census data to rapidly identify community-specific risk factors in a cost-effective manner.

Keywords

childhood obesity; economic hardship; electronic health records; health disparities; social determinants

Introduction

Childhood obesity is a leading public health concern, with recent data indicating more than one-third of US children and adolescents are overweight or obese (1). Excessive weight gain often persists into adolescence and adulthood (2, 3), significantly increasing the risk for other chronic diseases (4). While many risk factors are individual (e.g., genetics, behavior), multiple external factors are well recognized as contributors to obesity risk, including neighborhood walkability, safety, access to healthy food, and poverty (5). However, the contribution and relationship of these variables are not completely understood. Understanding how these factors interact to increase risk for obesity may inform the design of prevention and treatment approaches.

While childhood obesity is endemic to the US, disparate prevalence rates have been reported in certain subgroups (1), and these disparities may be widening. Multiple factors likely contribute to these differences, and poverty is emerging as a particularly important risk factor (6). Research describes a paradoxical positive association between poverty/food insecurity and childhood obesity, although recent data in both children and adults suggest these relationships may be more complicated than previously believed (7, 8). Other measures have been developed to characterize more completely the risk profile associated with poverty (beyond financial resources) at both the individual and community level. Specifically, the economic hardship index (EHI) was developed to capture multiple variables related to the stresses of low socioeconomic status for comparison among and within communities. EHI includes measures of crowded housing, dependency, education, per capita income, and unemployment in addition to community poverty rates. The recognition of the relationship of these external pressures to health suggests a consideration of EHI may be informative in the context of childhood obesity (9).

To better characterize the relationship of childhood obesity and EHI in communities, robust data collection and surveillance methods are needed. The utilization of de-identified electronic health record (EHR) data is particularly well suited to rapidly assess community health (10–12), as an EHR database provides a vast amount of information from pooled patient encounters collected during regular utilization of the healthcare system. Moreover, EHR-based assessment represents a shift from costly, time-consuming, and burdensome methods, such as on-site or telephone surveys and door-to-door data collection. The purpose of this study was to assess the relationship of childhood obesity and community-level EHI among a large sample of Wisconsin children using an EHR database linked with

community-level factors and to demonstrate EHR as an emerging tool for high-powered analysis of community health.

Methods

Database

The University of Wisconsin (UW) Public Health Information Exchange (PHINEX) links deidentified EHR data to community-level variables (e.g., neighborhood socioeconomic and demographic variables) as previously described (12). PHINEX includes records of patient encounters that occurred from 2007–2012 at UW primary care clinics serving mostly south-central Wisconsin. Census-defined block group level data (typically 600–3,000 individuals/group) were extracted from 5-year estimates of the US Census American Community Survey 2007–2011. In this study, 241 block groups containing ≥100 patients were included, representing 9 counties with urban, suburban, and rural areas. The study was reviewed and approved by the UW–Madison School of Medicine and Public Health Institutional Review Board.

Patient selection and missing data

The initial sample contained 102,231 patients ages 2–17 years. Patients were excluded from the analyzed sample for the following reasons: missing body mass index (BMI) measurement, missing race/ethnicity, missing EHI classification, and being associated with a block group with <100 patient records (Supplementary Figure 1). The resulting total sample consisted of 53,775 patients. Of the excluded patients, nearly half were excluded for being associated with a block group with sparse representation (i.e., few patients) rather than missing data in the patient record. Missing BMI, which occurred in 15.9% of patients, was significantly associated with age, race/ethnicity, and EHI, but not sex. Specifically, higher EHI, self-report as "non-Hispanic other" (compared to white patients), and younger age were associated with missing BMI ($p<0.001$ for all).

Individual level data

Patient data were collected during normally scheduled clinic visits. Variables included in this study were age, BMI (kg/m^2), sex, and self- or parent-reported race/ethnicity. Race/ethnicity was classified as non-Hispanic (NH) white, NH black, NH other, and Hispanic. According to the instructions for self-reported race/ethnicity, NH other can include (1) American Indians, Spanish American Indians, and Alaska Natives; (2) Asians (e.g., Chinese, Cambodian, Hmong, etc.); or (3) Native Hawaiians and Pacific Islanders. In our database, 99.5% of patients reported a race/ethnicity, of which 98.7 selected only one response. BMI was calculated from height and weight measured on the same day. All BMI values were plotted on age- and sex-specific growth charts to determine BMI percentile according to the CDC 2000 charts as follows: <5th percentile = underweight, 5th–85th percentile = normal weight, ≥85th to the 95th percentile = overweight, and ≥95th percentile = obese (13). If multiple patient encounters were available, the most recent BMI was used.

Community-level data

Patients were linked to census block groups using their geocoded address of residence. EHI score by block group was used as a measure of community-level socioeconomic status (14, 15). EHI is comprised of 6 measures: crowded housing (percent of housing units with >1 person/room), poverty (percent of households below the federal poverty level), unemployment (percent of people ≥16 years who are unemployed), education (percent of people ≥25 years without a high school education), dependency (percent of population <18 or >64 years), and per capita income. The calculation of EHI has been described previously [in Appendix 1 of Nathan and Adams, 1989 (16)]. Scores can range from 0–100, with 100 indicating the highest hardship. For this study, EHI was normalized for all Wisconsin block groups.

Statistical analyses

Rates of obesity were reported overall, by age, and by race/ethnicity. Rates of obesity and EHI scores were summarized for each census block group rather than linking values for each individual patient record. Pearson correlation coefficients were used to determine the correlation between EHI and obesity overall, by age, and by racial/ethnic groups at the census block group level. Mixed-effects modeling was used to examine the association between childhood obesity rate and EHI controlling for demographic variables and interactions based on the methods of Shih et al (9); block group was included as a random effect. Only significant interaction terms were retained in the final model. For significant interaction terms, simple linear regression analyses were performed for individual subgroups (e.g., age or racial/ethnic groups) to determine the association between the variables of interest. When correlation or regression analyses were performed on these subgroups, only block groups with ≥20 patients in the selected subgroup (e.g., the 2–4 year age group) were included. For all block group-level analyses, the obese children were compared to all non-obese children. All analyses were performed using SAS version 9.3 (Cary, NC), and the significance level was set at 0.05.

Results

Patient demographics

In total, 53,775 children ages 2–17 years from 241 census block groups were analyzed (52.2% male) (Table 1). The children were categorized as follows: underweight, 3.5% (n=1,899); normal weight, 70.0% (n=37,634); overweight, 14.8% (n=7,953); and obese, 11.7% (n=6,289). The prevalence of obesity significantly increased with age (2–4 years, 7.8%; 5–11 years, 11.7%; 12–17 years, 13.7%, $p<0.05$) and differed among the included racial/ethnic designations (NH white, 10.0%; NH other, 10.5%; NH black, 19.8%; Hispanic, 21.3%, $p<0.05$). Among the 241 included block groups, childhood obesity prevalence ranged from 2.0 to 32.6%.

EHI and obesity

The mean EHI for the included block groups was 24.6 (range, 13.3–49.4). EHI was significantly associated with childhood obesity rates (r=0.62, $p<0.0001$) (Figure 1).

Moreover, mixed effects modeling indicated a significant interaction between EHI and both race/ethnicity (p=0.0496) and age (p=0.035) on obesity rates in the initial model. Sex was not a significant term and was removed. Because race/ethnicity was a significant term, separate models were run for each race/ethnicity. For these individual analyses, EHI was significantly associated with obesity rates for patients identified as NH white (r=0.51, p<0.0001) and NH other (r=0.55, p<0.0001) but not for NH black (r=0.05, p=0.65) or Hispanic (r=0.18, p=0.16) patients. Moreover, the race/ethnicity-specific regression analyses demonstrated significant racial/ethnic differences in the slope for obesity rate and EHI (NH white, β=0.48, p<0.001; NH black, β=0.07, p=0.65; NH other, β=0.48, p<0.001; Hispanic, β=0.22, p=0.16) (Figure 2).

Similar to race/ethnicity, separate models were run for the three age groups. EHI was significantly associated with obesity rate in all three age groups, with age-specific regression modeling demonstrating an amplified effect of EHI with increasing age (2–4 years, β=0.35, p<0.001; 5–11 years, β=0.70, p<0.001; 12–17 years, β=0.69; p<0.001) (Figure 3).

Discussion

In this study, we demonstrated the relationship of childhood obesity and economic hardship among Wisconsin children using PHINEX, which linked deidentified patient-level data from electronic health records with community-level data. We determined economic hardship was positively associated with childhood obesity prevalence and that this association was modified by race/ethnicity and age. Specifically, the association was significant for patients identified as NH white and NH other but not for Hispanic and NH black patients, who had consistently high obesity rates across all levels of economic hardship. Moreover, we detected a significant interaction between EHI and age on obesity rates, with the effects of economic hardship amplified in older children compared to the youngest group (2–4 years old).

To our knowledge, we are only the second group to examine economic hardship index (EHI) in relation to childhood obesity (9). Using the same composite index, Shih and colleagues similarly reported EHI was positively associated with childhood obesity rates in Los Angeles (LA) county, with the highest rates in the communities with the highest economic hardship (9). These authors also found the relationship between EHI and childhood obesity was modified by race/ethnicity, which aligns with the results from our analysis. LA county is notable for significant diversity in both racial/ethnic backgrounds and socioeconomic conditions. While diversity in both of these factors exists to some extent in Wisconsin, the LA county sample was predominantly Hispanic (68.7%), whereas the PHINEX dataset was predominantly NH white (77.4%). Although EHI values cannot be directly compared because of normalization within each dataset, we calculated a much narrower range of EHI scores (range 13.3–49.4, median=25.3, mean=25.6) than reported by Shih et al. (range 14.0–81.4, median=46.0, mean=44.6). However, our results regarding race/ethnicity and EHI were very similar, despite differing EHI distributions and different data collection methodology (i.e., collected during primary care visits). While our convenience sample represents only children who accessed primary care, it did not require significant data collection efforts or financial support. This approach represents a more cost-effective and

sustainable method that enables rapid data turn-around for community action related to obesity prevention efforts (17). Moreover, our results suggest the utility of considering obesity rates in the context of community economic hardship.

The link between poverty and health outcomes has been well established, but EHI may be particularly useful for potentially capturing lesser-understood determinants of obesity risk, such as stress (reflected by family unemployment) (18) and sleep conditions (reflected by crowded housing) (19). Several large epidemiological studies have shown that childhood socioeconomic conditions were associated with future disease risk, including increased mortality for children in adverse socioeconomic situations independent of their socioeconomic status as adults (20). Other studies suggest higher economic hardship in childhood predicts entry into work groups with higher disease risk, such as manual and unskilled work (21). Overall, these studies highlight childhood as an important therapeutic window to intervene and reduce future disease risk.

Unlike Shih et al., we found a significant interaction between age and EHI on obesity, suggesting the effects of economic hardship increase with age. Of note, our study population was across a much wider range of ages (2–17 years compared to 5^{th}-7^{th} graders, who are typically 10–15 years old), which may have captured differences in the relationship between age and hardship. Our findings may suggest a compounding of adverse conditions on the growing child. In fact, a recent longitudinal study found the "accumulation of poverty" was significantly associated the obesity, and this relationship was modified by race/ethnicity (22). However, it is unknown if the effects of the other factors captured in EHI (beyond poverty) are similarly compounded over time. Another study among low-income children found that cumulative hardship was associated with decreased wellness (23). However, a different hardship index was used, and obesity was not specifically considered. Because these effects may be modified by age, additional longitudinal studies are needed to characterize these relationships more completely.

Similar to what was reported in LA county (9), the association between EHI and obesity was different among racial/ethnic groups, suggesting cultural and/or genetic mediators. Specifically, the association was significant for NH white and NH other children, but *not* for Hispanic or NH black children. The difference could be related to multiple factors, particularly family or cultural views on diet, activity, and weight. For example, a study of a school district in Arkansas found that the majority of parents (60%) failed to recognize overweight in their children, and that African American parents were more than twice as likely to underestimate weight status in their overweight children compared to white parents. Moreover, the authors reported no difference in accuracy of weight estimation by education level or socioeconomic status (24). Another study, Project Viva, followed children from the prenatal period and found the risk of becoming overweight/obese at age 7 was attenuated for NH black and Hispanic children after controlling for infant feeding, early health behaviors, socioeconomic factors, and parental health (25). These findings suggest that racial/ethnic differences in both weight perception and health behaviors may be contributing factors to more consistent childhood obesity rates across a range of EHI scores.

Our PHINEX dataset has several features that represent the strengths of our EHR-based approach. Although the records in PHINEX were predominantly from NH white patients in south-central Wisconsin, PHINEX has been shown to be representative of Wisconsin's demographics (12) and in the context of other chronic diseases, such as asthma (26). Moreover, the large number of patient records provided sufficient power to examine individual factors related to childhood obesity in the less well-represented racial/ethnic subgroups. Moreover, the longitudinal data contained within the ever-expanding PHINEX database will allow trends to be tracked over time and the response to public health or community-level interventions to be more easily measured in the future.

We suggest that deidentified EHR data linked with census-type data can be used to better understand community health, such as the example described in this study. However, this approach has several limitations. First, EHI and obesity prevalence were considered at the census block level rather than the individual level, and the coefficient of variation for data at the census block level can vary widely. Moreover, maternal factors known to be important contributors to childhood obesity risk (e.g., weight status, weight gain during pregnancy, smoking, duration of breastfeeding) were not examined because the deidentified nature of the health records did not allow parent and child records to be linked. However, unlike the LA county study that matched children's anthropometric data to their school, the individual data from our EHRs were linked to patient residence, which may better account for home living conditions experienced by the children.

In the context of obesity, there was a potential for systematic biases in the data, as BMI was more likely to be missing in those living in census block groups with the highest EHI scores. Moreover, BMI was more likely missing for NH other patients compared to white patients; the "other" category is heterogeneous, which makes it difficult to comment on the reasons for the missing data. Age biases may also exist, as missing BMI data was higher with younger patients, highlighting the need for increased awareness of weight tracking during the early childhood period. Moreover, when we examined the childhood obesity prevalence estimates for the entire PHINEX sample (n=93,130) for 2011–2012 to rates from the National Health and Nutrition Examination Survey 2011–2012 (NHANES) (27), we observed similar age, sex, and racial/ethnic group relative risk differentials even though over 37% of potentially eligible patients had missing BMIs. This comparison suggests that elaborate adjustments for missing data are not needed for childhood obesity risk (*Flood et. al, manuscript submitted for publication*). More widespread adoption of the "meaningful use" criteria designed to incentive implementation and improvement of EHR systems will likely improve data quality and reduce missing data in the future (28).

The factors contributing to obesity prevalence are extremely complex, and EHI represents only a component of obesity risk. However, our study suggests that the relationship between EHI and its interaction with race/ethnicity that was uncovered in LA in regards to childhood obesity is also evident in Wisconsin, suggesting the utility of this composite index score in measures of health. Despite the limitations mentioned, we demonstrated the feasibility of using EHR-based methods, which represent a substantial savings of both time and financial resources compared to traditional data collection methods (17). In summary, the PHINEX dataset enabled an examination of patient-level demographic information aggregated within

defined geographic boundaries and for assessment of factors that may contribute to childhood obesity. Understanding how these factors act individually and in combination will allow researchers, practitioners, and public health professionals to tailor intervention programs to local communities and at-risk populations.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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What is already known about this subject

- Community-level factors contribute to risk for childhood obesity
- Specifically, poverty and other components of economic hardship underlie childhood obesity risk
- Race/ethnicity modify the relationship between economic hardship and childhood obesity

What this study adds

- Age also modifies the relationship between economic hardship and obesity
- The modifying effect of race/ethnicity on the relationship between economic hardship and childhood obesity prevalence persists in varied populations
- Electronic health record data linked with community-level variables is a novel method of rapid assessment of community-level factors related to health outcomes

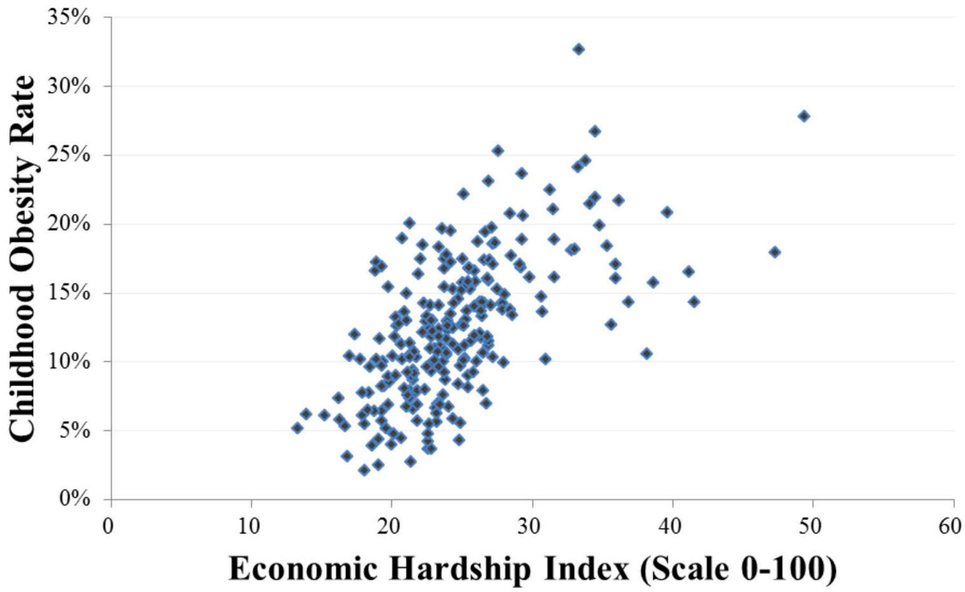

Figure 1.
Economic hardship index is associated with childhood obesity rate at the census block group level (n=241 block groups with a minimum patient denominator of 100) as determined by Pearson correlation coefficients.

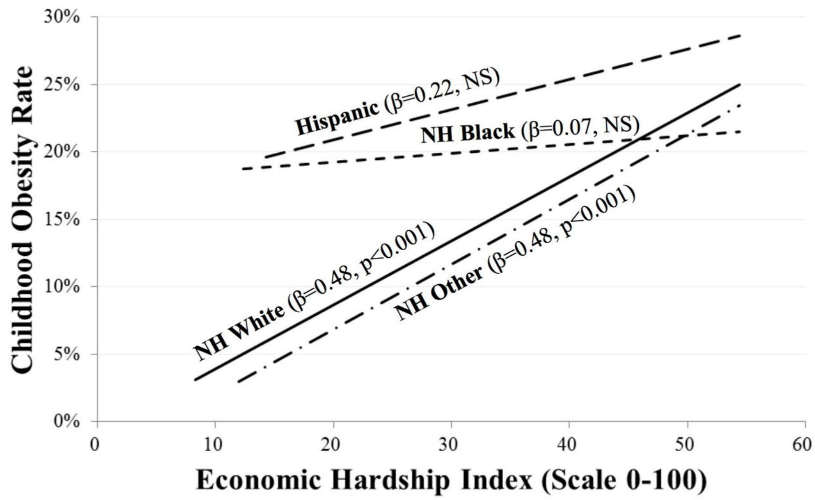

Figure 2.

Race/ethnicity significantly modifies the relationship between economic hardship index and childhood obesity rate at the block group level. A significant interaction was determined for race/ethnicity in the mixed effects model, so simple linear regression analyses were conducted for each subgroup (e.g., Hispanics). Block groups with a minimum of 20 patients for the group under consideration were included in the analysis. NH, non-Hispanic.

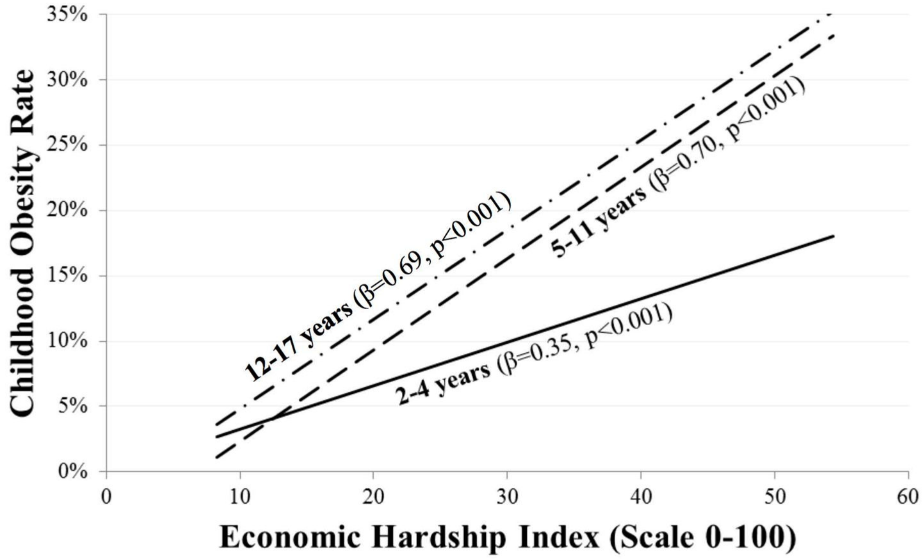

Figure 3.

Age significantly modifies the relationship between economic hardship and childhood obesity at the block group level. A significant interaction was determined for age in the mixed effects model; therefore, simple linear regression analyses were conducted for each subgroup (e.g., 2–4 year old age group). Block groups with a minimum of 20 patients for the group under consideration were included in the analysis.

Table 1

Childhood obesity rates in the study sample overall and by sex, age, race/ethnicity, and EHI.

	Obesity Rate, % (95% CI)	Number Obese, n	Total, n (% of total)
Sex			
Male	13.0 (12.6–13.4)	3,640	28,066 (52.2%)
Female	10.3 (9.9–10.7)	2,649	25,709 (47.8%)
Age group			
2–4 years old	7.8 (7.3–8.4)	839	10,688 (19.9%)
5–11 years old	11.7 (11.3–12.1)	2,731	23,289 (43.3%)
12–17 years old	13.7 (13.3–14.2)	2,719	19,798 (36.8%)
Race/Ethnicity			
White (NH)	10.0 (9.7–10.2)	4,144	41,624 (77.4%)
Black (NH)	19.8 (18.7–20.9)	954	4,814 (9.0%)
Other (NH)	10.5 (9.5–11.6)	364	3,457 (6.4%)
Hispanic	21.3 (20.0–22.6)	827	3,880 (7.2%)
EHI quartiles			
1st	8.8 (8.3–9.2)	1,262	14,421 (26.8%)
2nd	9.7 (9.2–10.2)	1,418	14,644 (27.2%)
3rd	12.5 (11.9–13.0)	1,617	12,956 (24.1%)
4th	16.9 (16.3–17.6)	1,992	11,754 (21.9%)

NH, non-Hispanic; EHI, economic harship index.