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ORIGINAL RESEARCH

Exploring Walking Path Quality as a Factor for Urban Elementary School Children's Active Transport to School

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***Background*:** Path quality has not been well studied as a correlate of active transport to school. We hypothesize that for urban-dwelling children the environment between home and school is at least as important as the environment immediately surrounding their homes and/or schools when exploring walking to school behavior. ***Methods*:** Tools from spatial statistics and geographic information systems (GIS) were applied to an assessment of street blocks to create a walking path quality measure based on physical and social disorder (termed "incivilities") for each child. Path quality was included in a multivariate regression analysis of walking to school status for a sample of 362 children. ***Results*:** The odds of walking to school for path quality was 0.88 (95% CI: 0.72–1.07), which although not statistically significant is in the direction supporting our hypothesis. The odds of walking to school for home street block incivility suggests the counter intuitive effect (OR = 1.10, 95% CI: 1.08–1.19). ***Conclusions*:** Results suggest that urban children living in communities characterized by higher incivilities are more likely to walk to school, potentially placing them at risk for adverse health outcomes because of exposure to high incivility areas along their route. Results also support the importance of including path quality when exploring the influence of the environment on walking to school behavior.

***Keywords*:** environment, geographic information system (GIS), incivilities, kriging

Active transport to school, which includes walking, bicycling and other forms of nonmotorized travel, has been an increasingly popular subject of research driven largely by efforts to combat the epidemic of obesity among youth.[1-11] Research indicates that children who walk and bike to school are more likely to meet their recommended daily levels of activity and have higher aerobic capacity than youth who travel by car or bus.[12-14] Although the scientific evidence linking active transport and reduced obesity is expanding, overall, the research suggests benefits for children's health including improved cardiovascular health and fitness, reduced symptoms of depression and anxiety, and better academic performance.[15]

Studies on children's physical activity have increasing urgency since rates of physical activity among youth have continued to decline as overweight and obesity among youth rise.[16-19] Active transport represents an important opportunity to increase physical activity.[13,20-21] Much evidence has been gathered on determinants of active transport to school for children with specific focus on environmental determinants.[12,22-26] Factors consistently showing evidence associated with walking to school include distance to school, economic factors such household income and car ownership, as well as built environment variables such as the existence and quality of walking and biking paths[27].

Central to the discussion of active transport is how the built environment is conceptualized and measured. A comprehensive review described 3 types of environmental measurement methodologies most often used in studies of the environment and physical activity.[28] These include 1) perceptions of the environment which are obtained by surveying study participants,[2,29–31] 2) objective audits of the environment based on direct observation by researchers,[32–35] and 3) existing environmental databases which are usually developed for urban planning, transportation, or other municipal purposes.[36-39] While several tools such as geographic information systems (GIS) have the potential to advance the literature on the built environment and

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physical activity, their application to research has only recently been published.

In this paper, we use the 3 categories of methods described by Brownson and colleagues to develop and evaluate environmental determinants of walking to school behavior combined with other measures for a sample of children in an urban setting. We chose to include all 3 of these methods since they have been used in prior research on the built environment and walking to school, but specifically highlight/examine the importance of using an objectively derived measure of walking path quality. Previous research by our team reported on a measurement of physical and social disorder (termed incivility) on the street block where children live and distance to school (straight line Euclidean distance), as the primary factors of interest when describing walking to school behavior.[40] Street block incivility is defined as disorderly conditions such as the presence of alcohol bottles, broken windows, trash, and fighting (see Methods). Expanding on this prior study, in the current study we consider not only the environment surrounding children's home, but also the environment between homes and schools via along identified paths to school. We hypothesize that walking path quality, based on objectively-derived measurements of incivility, calculated for identified paths to school for each child will more accurately reflect children's walking to school status than similar environmental measures just around children's homes and/or schools as in methods used previously.

Spatial statistical tools were applied to data from an objective street block level audit and GIS information of road networks to create a walking path and a measure of walking path quality based on incivilities for each child participant. The newly developed path quality metric is then included in a multivariate regression analysis of walking to school status with additional variables (eg, GIS derived path distance and parent perception on neighborhood safety) for the sample of children. Our use of advanced spatial statistical methods combined with GIS provided the necessary tools to use and combine these concepts for use in the walking to school analysis, which was a new component to existing research in this area.[41] The fields that have made the most progress measuring the built environment—such as planning and applied geography—have not necessarily focused these efforts on illuminating physical activity patterns or behavior. Furthermore, the combination of travel behavior and physical activity data remains rare.

Several studies in the extant literature support the analytic approach that we employed[1,22,36,38,42,43] and expressly encourage the use of objectively-derived measures of the built environment that can be directly linked to an individual's routine activities. For example, Pont et al[22] and Forsyth et al[38] argue for increased use of GIS related to objective measures of the physical and economic environment. In Panter et al,[1] objectively measured neighborhood factors and route attributes obtained using a traditional GIS database were both found to be associated with active transport. In Guo[36] and Guo and Ferreira Jr.,[42] individual path data were shown to affect the utility of walking, while Brown et al[43] provides support for utilizing individual en route walking experiences.

Methods

Data

The *Neighborhood Inventory for Environmental Typology* (NIfETy) is a street block level auditing instrument used to objectively collect observational data on violence, alcohol, and other drugs (VAOD) and the physical and social environment.[44] In addition to the VAOD measures, the NIfETy includes domains for physical layout, type of structures, physical and social order/disorder, as well as adult and youth activity. Most of the approximately 160 NIfETy items are direct counts (eg, # of dwellings, # of men loitering), categorized counts (eg, # of intoxicated people: 0, 1–3, 4–7, 8 or more), or binary indicators (eg, obvious signs of drug selling: yes or no). To perform the audit trained teams of raters collected information for the various domains by traversing the block a minimum of 3 times. Further details on data collection and metrics (reliability and validity) for the NIfETy instrument are reported elsewhere.[32,44]

The NIfETy instrument has been used for several studies in Baltimore City.[29,32,40,44-48] Data from 3 sampling waves were combined to create the NIfETy data used here, comprising n = 1173 sampled street blocks assessed in July 2007 to October 2007.[49] The street block level incivility score, previously used,[40] was used as a summary score for the physical and social environment variables in the NIfETy study. Incivility is calculated by summing 49 items from the VAOD (eg, police tape/outlines, alcohol bottles, syringes), physical disorder (eg, broken windows, trash, graffiti), and social disorder (eg, people fighting, evidence of prostitution) NIfETy domains yielding a continuous measure of incivility for each of the n = 1173 sampled Baltimore City street blocks. The specific list of all NIfETy items used to calculate street block incivility and details on their contribution to the summary measure are reported elsewhere.[44,49]

The *Multiple Opportunities to Reach Excellence* (MORE) Project is a longitudinal epidemiological study primarily designed to assess the impact of long term exposure to community violence on youth in Baltimore City, an urban area with over 600,000 residents and a homicide rate close to 7 times the national rate.[29] The study participants are children in grades 2–5 attending 6 Baltimore City public schools. To ensure variability in violence levels, schools from low, moderate, and high violence areas were considered. The principals of 8 schools were invited to participate and 2 principals declined, resulting in 6 total schools, 2 for each violence strata. Within each school, all eligible children and parents were invited to participate. Eligibility criteria were 1) enrolled full time in grades 2–5, 2) age 8–12 years, and 3) speak English and live with an English-speaking parent/guardian. Children with serious medical or neurological illness or not living with at least 1 parent/guardian were excluded. In-person computer assisted programmed interviews were conducted at school with participating children; parents were interviewed via telephone. Data were collected on demographics, child activity (including child and parent reported walking to school behavior), perceptions of the surrounding neighborhood and several other areas related to exposure to violence.[29] The final MORE Project data set used for the current analysis contained information from 362 children collected in August 2007 to October 2007.

In addition to the NIfETy and MORE Project data sets, several additional data sources were used. These data sources were used for geocoding, to support the spatial prediction models for incivilities, and to augment the individual level MORE Project data with several neighborhood level variables. 2007 TIGER/Line (copyright) streetline shapefiles were used along with accompanying tables available from the US Census Bureau (US Census Bureau, 2008). To verify the geographic placement of street centerlines, addresses, and schools, 1-m resolution natural color ortho-imagery from the 2007 National Agricultural Imagery Program (NAIP) was obtained through the Maryland Department of Natural Resources (US Department of Agriculture Aerial Photography Field Office, 2007). Neighborhood Statistical Area (NSA) boundaries and aggregated demographic and socioeconomic information for 2000 were also obtained from the U.S. Census Bureau. NSAs are a special aggregation unit formed in collaboration with the Baltimore City Planning Department. They are designed to more closely reflect community neighborhood identities than traditional aggregation units such as census block groups or tracts. Three socioeconomic indicators at the NSA level were used: percent of the population below the federal poverty level, percent of the population with at least a high school degree, and median household income.

GIS Methods

ArcGIS 9.3[50] was used to combine all available data sources and to perform the various spatial data manipulations needed for analysis. A street map was developed based on the 2007 TIGER/Line shapefiles. The TIGER shapefiles containing the location of streets, rail lines, and other passages in Baltimore City were merged with an accompanying relationship table containing information about street name, direction, zip code, and address ranges for each street block as well as indicator fields for type of linear feature (road, rail, other). Utilizing these indicator fields, the data set was narrowed to include only road segments. The accuracy of the street center lines was visually assessed by layering the created street map over the 2007 NAIP imagery data. An address locator file was created within ArcGIS for geocoding.

Spatial information from the NIfETy data contained a street block range rather than a specific home address. For purposes here, geocoding was performed to the lowest available address within the given street block range. Four sampled street blocks could not be reconciled yielding the n = 1173 NIfETy sample street blocks reported above. The MORE Project data contained students home address information, which were geocoded to the streetmap. Of the 365 MORE Project home addresses in the original data set, 362 were successfully geocoded and included in the final data set. Three records were removed due to missing information on their respective school attended or the inability to reconcile the geocoding with the address provided. Before geocoding all spatial data (addresses and street block ranges) were customarily cleaned and standardized.[49]

The centroid for each Baltimore City street block segment was calculated and the geocoded NIfETy sampled street block incivility values were geocoded to this GIS layer. These data were then used to spatially predict incivility values at unsampled street blocks represented by their centroid coordinates (see subsequent text). A network data set containing street segments, junctions, connectivity rules, and block quality variables was constructed from the TIGER streetmap with both the sampled NIfETy and spatially predicted incivility values attached. The MORE Project data were separated by school. For each school the shortest path between the child's geocoded address and the school was calculated using the network data set and the Network Analyst extension of ArcGIS.[51]

Network Analyst determined the shortest path to school (traversed along road networks) and then aggregated the road lengths and path incivility scores along these paths for each child. Path to school incivility scores were aggregated by averaging street block incivilities (completed via spatial prediction) for all street blocks along each identified path. For blocks that were only partially traversed, a partial incivility score proportional to the traversed segment was assigned. The average incivility score, which we refer to as walking path quality, for path K was calculated as

$$q_k = \gamma \cdot \frac{\sum_i b_i p_i}{\sum_i l_i p_i} \tag{1}$$

where $i = 1, \ldots, n_k$ is an index of the street blocks traversed along path K, b_i and l_i are the street block incivility and length for the i^{th} block, respectively, p_i values between 0 and 1 is the proportion of the block traversed along the path, and γ is a scaling factor included for interpretability. For example, if γ = 100 feet, then q_k is the average path quality per 100 feet. The walking path quality and length data for each child was exported, formatted, and joined to the MORE Project data using unique identifiers. The completed data set was exported from ArcGIS for follow up analysis.

Statistical Analysis

Spatial data manipulations via GIS provided the necessary data to perform 2 statistical analyses. The first involved spatial prediction of incivility values at NIfETy unsampled street blocks so a walking path quality variable could be calculated for each child's path to school. The second analysis used this walking path quality variable in a regression as a determinant for explaining children's reported walking to school behavior.

Geostatistics provides well established methodology for spatial prediction.[52-54] Based on the n = 1173 sampled incivility data an ordinary kriging model was used to predict incivility values at the remaining street block centroids in Baltimore City for the street blocks that were not part of the NIfETy survey. Note predicted incivility values were only needed for street blocks along each child's generated path to school. However, incivility was mapped via kriging for all of Baltimore City for completeness. Under the ordinary kriging model, predicted incivility at unsampled street blocks are weighted averages of all the 1173 incivility measurements calculated for those streets in the NIfETy survey, with higher weight given to those sampled measurements closer to each prediction location. The strength and type of spatial dependence governs this weighting scheme, which is characterized using the geostatistical variogram function. The variogram, which is a function of distance, and its parameters (range, sill, and nugget in geostatistical terminology) fully characterize spatial dependence for use in kriging.

Empirical variograms were estimated based on the sample incivility data. Directional variogram estimates were computed and used to visually assess the assumption of isotropy, which states that spatial dependence is a function only of distance between locations rather than a function of distance and direction. Parametric variogram functions (gaussian, Matern, exponential and spherical) were fit to all empirical estimates using nonlinear weighted least squares,[54] and their plots and values of Akaike's information criterion (AIC)[55] were compared. Based on these comparisons, a final variogram function was selected and used to estimate the kriging weights for the ordinary kriging predictor. Cross validation was run to validate the results of the kriging process.

The second analysis was designed to quantify the newly created average path quality variable (henceforth referred to as walking path quality variable) as a determinant for walking to school. To begin, the path quality variable was explored by calculating descriptive statistics and correlations with other potentially associated variables. Next, each variable potentially associated with walking to school (including walking path quality) was examined in both univariate and multivariate logistic regression models with child reported walking to school as the outcome. Likelihood ratio tests were performed to check the significance of included regression covariates.[56]

Based on the results of the univariate logistic regression models and literature review, a full multivariable model was specified. The general form of the model is below:

$$\text{logit}(P(Y=1))=\beta_0 + \beta_1 X_1 + \ldots + \beta_0 X_p$$

where Y represents the child walking to school binary outcome with Y = 1 indicating that the child reported walking to school, Y = 0 otherwise, $X_1, \ldots, X_p$ represent the values of the individual and area level covariates for each child and $\beta_1, \ldots \beta_p$ represent the log odds ratio associated with the corresponding variable. The full model included all variables that were significant in the univariate logistic regression analysis or identified as having at least a potential association based on relevant literature. Diagnostic procedures were performed to check the model fit and assumptions. Residuals were also examined for spatial correlation.

Area level covariates based on NSA demographics and socioeconomic status variables were also considered as potential model covariates in addition to covariates specific to each child. When included, regression inference was based on a Generalized Estimating Equations (GEE) approach, which accounted for correlation (clustering) within NSAs.[57-58] Missing values for parent education and income level were imputed by regressing the parent variables on child demographics and neighborhood variables. The missing parent variables were replaced using the predicted values from these regression equations. In addition variograms were estimated for residuals from all final models and interpreted here with no evidence of residual spatial variation.

All geostatistical modeling and analysis was performed in R statistical computing environment, version 2.10.1[59] using the R contributed packages gstat[60] and geoR[61] and then exported back into ArcGIS for mapping. Regression analysis for walking to school behavior was also performed in R using contributed package geepack[62] for the GEE based inference.

Results

Figure 1 displays maps for the NIfETy and MORE Project data sets. The map on the left shows the street block centroids for streets blocks that were sampled using the NIfETy instrument for which incivility values were subsequently calculated. The map on the right displays the geocoded home addresses for the 362 children as well as locations for each of the 6 participating schools. Also identified in these maps are the 60 Baltimore City NSAs, the area unit used in the regression analysis for exploring further neighborhood effects of walking to school behavior. Table 1 summarizes the individual child level variables from the MORE Project data set and area level variables for included NSAs. All variables listed were considered candidates in the regression analysis.

Mapping street block level incivilities (spatial prediction) from the NIfETy data involved calculating the empirical variogram, fitting a parametric variogram function, and using the kriging weights calculated under the ordinary kriging model to predict incivility at street blocks. Plots of variogram estimates (plots not shown) demonstrated spatial dependence in the incivility data up to about 3 miles, so incivility values for street blocks further than 3 miles apart appeared spatially uncorrelated. Visual inspection of directional variograms revealed no substantial departures from one another, therefore spatial dependence was assumed isotropic.

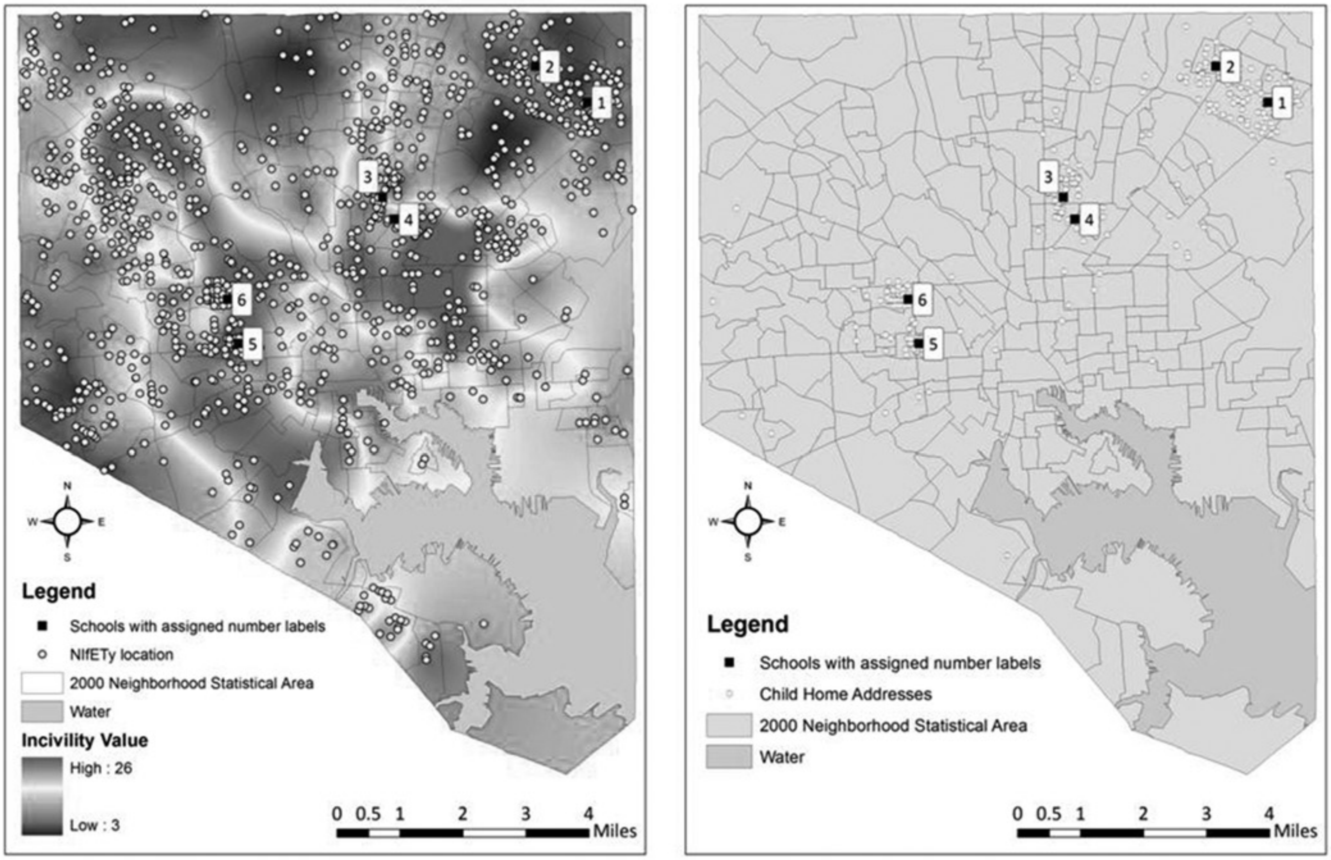

Figure 1 — The n = 1173 Neighborhood Inventory of Environmental Typology (NIfETy) sample locations (Left). The background shading in this map are the results from the kriging analysis to spatially predicted incivility values. Multiple Opportunities to Reach Excellence (MORE) Project schools and geocoded home addresses for the 362 participating children (Right). Identified in both maps are the 60 Baltimore City Neighborhood Statistical Areas (NSAs) from the 2000 Census.

The spherical parametric variogram provided the best fit to the empirical variogram estimates and was the chosen variogram function used for kriging. Complete details of the kriging analysis and results are reported elsewhere.[49]

A map of 50-ft^2 grid cells was overlayed onto the Baltimore City map and ordinary kriged predictions of incivility were generated for each grid cell. These predicted incivility values are shown mapped in Figure 1 and displayed as the background shading. Predicted incivility ranged from around 3.06–26.12. The mean square normalized error computed under n-fold cross-validation was 0.895, reasonably close to the optimal value of 1.0.[63] Because of the NIfETy sampling scheme, areas around the 6 schools were more intensively sampled than other areas, leading to more precise estimates in these areas. This supports a method like kriging to predict incivility for use in the walking path quality variable since the MORE Project children and their identified paths to school are also clustered around their respective schools.

The predicted incivility values provided the data necessary to generate the walking path quality variable from equation (1) since not all street blocks for each child's identified path to school were surveyed with the NIfETy instrument. Actual values and summary statistics of walking path quality (average incivilities along identified paths) and home street block incivilities are not reported since they are used more in a relative sense to measure physical and social disorder and by themselves do not retain much interpretation appeal. Correlation between home street incivility and the walking path quality variable was 0.65. The average path distance was about 0.7 of a mile, compared with a mean of just under 0.6 of a mile for the straight line distance.

The results of the univariate logistic regression analyses of child reported walking to school are listed in Table 2. In these analyses, age in months, child free and reduced meal status, school, parent education and income, parent perception of neighborhood safety, walking path length, walking path quality, incivilities for the home block, and all 3 NSA level variables (median income, percent below poverty level, and percent with at least a high school education) were significant ($P < .05$). Since walking path quality, defined as the average incivility along the identified paths, is of focal interest it should be noted that the odds ratio for walking path quality and the home street block incivility were 1.15 and

Table 1 Summary of Individual (From the MORE Project) and Neighborhood Statistical Area Variables Utilized in the Walking to School Analysis

MORE project variables	N	Mean (Std. Dev.)
Age (years)	362	960 (1.04)
Age (months)	362	123.60 (12.42)
Walking path length (feet)	362	3702.44 (4919.78)
Walking path quality (per 100 ft)	362	4.88 (2.76)
Incivility for home street block	362	12.64 (7.14)
Male (proportion)	167	0.46
African American	313	0.86
Neighborhood is safe (child perception)	268	0.74
Neighborhood is safe (parent perception)	100	0.28
Child feels safe at home	249	0.69
Grade (proportion)		
2nd	9	0.02
3rd	127	0.35
4th	123	0.34
5th	103	0.28
Parent education level (proportion)		
High school or less	128	0.35
Some college	69	0.19
College or greater	26	0.07
Missing	139	0.38
Parent annual household income (proportion)		
Less than $5000	30	0.08
Between $5000–$9999	22	0.06
Between $10,000–$19,999	37	0.10
Between $20,000–$29,999	42	0.12
Between $30,000–$39,999	52	0.14
Between $40,000–$49,999	39	0.11
More than $100,000	7	0.02
Missing	133	0.37
How safe are the neighborhoods on the way to school? (child perception; proportion)		
Very safe	131	0.36
Safe	137	0.38
A little safe	66	0.18
Not safe at all	26	0.07
Missing	2	0.01
Child free and reduced meals (proportion)		
No free or reduced meals	52	0.14
Free lunch	247	0.68
Reduced meals	46	0.13
Missing	17	0.05
Neighborhood statistical area variables		
Children per tract	60	6.03 (9.80)
Median income (dollars)	60	$31,405.98 ($14,077.10)
% with high school degree or greater	60	8.08 (12.98)
% below poverty level	60	21.53 (12.71)

Note. Mean and Standard Deviation (Std. Dev.) are listed for continuous variables, while proportion is listed for categorical variables. N is a count of the number of units in the sample for continuous variables or the number in the category for categorical variables.

Table 2 Univariate Logistic Regression Odds Ratios, 95% Confidence Intervals (CI) for Child Reported Walking to School and *P*-Values From Likelihood Ratios (LR) Tests

Variable	Odds ratio	95% CI	LR test *P*-value†
Male	1.228	0.808–1.869	0.3351
Age in months (centered)	1.021	1.004–1.039	**0.0150**
African American	1.368	0.746–2.511	0.3089
Is neighborhood safe? (child)	0.901	0.556–1.451	0.6705
Is neighborhood safe? (parent)	3.375	2.031–5.769	**0.0001***
Does child feel safe at home?	0.808	0.512–1.266	0.3536
Walking path length (500 ft)	0.941	0.914–0.968	**0.0001***
Walking path quality (per 100 ft)	1.145	1.054–1.250	**0.0117**
Incivility for home street block	1.090	1.056–1.126	**0.0001***
NSA—median income ($1000)	0.971	0.951–0.989	**0.0117**
NSA—% below poverty level	1.042	1.022–1.062	**0.0001***
NSA—% > high school education	0.954	0.934–0.973	**0.0001***
School			**0.0002**
School 2 (vs. School 1)	0.489	0.234–1.006	
School 3 (vs. School 1)	1.106	0.560–2.183	
School 4 (vs. School 1)	0.518	0.233–1.130	
School 5 (vs. School 1)	2.264	1.004–5.319	
School 6 (vs. School 1)	1.826	0.908–3.712	
Grade			0.8407
Grade 3 (vs. Grade 2)	0.594	0.121–2.359	
Grade 4 (vs. Grade 2)	0.598	0.122–2.375	
Grade 5 (vs. Grade 2)	0.690	0.139–2.774	
Parent education level			**0.0001***
Some college (vs. < high school)	0.395	0.252–0.616	
College or higher (vs. < high school)	0.307	0.127–0.708	
Free and reduced meals (FARM)			**0.0343**
Reduced meals (vs. non-FARM)	1.757	0.791–3.958	
Free lunch (vs. non-FARM)	2.214	1.210–4.122	
Parent annual household income			**0.0002**
$5000–$9999 (vs. < $5000)	2.250	0.626–9.369	
$10,000–$19,999 (vs. < $5000)	0.805	0.310–1.982	
$20,000–$29,999 (vs. < $5000)	0.428	0.172–0.996	
$30,000–$49,999 (vs. < $5000)	0.316	0.123–0.758	
$50,000–$99,999 (vs. < $5000)	0.616	0.218–1.668	
More than $100,000 (vs. < $5000)	0.071	0.003–0.498	
How safe are the neighborhoods on the way to school? (child)			0.2883
Safe (vs. very safe)	0.636	0.390–1.032	
A little safe (vs. very safe)	0.823	0.451–1.505	
Not safe at all (vs. very safe)	1.032	0.439–2.523	

† Values in bold are significant at $\alpha = .05$.

* Indicates $P < 0.0001$.

Abbreviations: NSA, neighborhood statistical area.

1.09, respectively, both suggesting the counter intuitive notion of increased likelihood of walking for increased levels of incivility. For the home street block incivility variable similar results were also found previously.[44]

Table 3 shows the results from the final GEE model controlling for clustering within NSA. Parent perception of neighborhood safety, receiving reduced meals at school, increases in incivilities for the home street block, median NSA income were significantly associated with higher odds of walking. Parent annual income of more than $100,000, walking path length, and attending school 4 were significantly associated with lower odds of walking. Although not significant, the odds ratio for walking path quality from this final model was 0.88 (95% CI: 0.72–1.07, P = .19) which is in the direction supporting our hypothesis that higher incivilities along a path to school associate with less likelihood of walking to school. Furthermore, the odds ratio for the home street block incivility variable of 1.10 (95% CI: 1.08–1.19, P = .01) still suggests the opposing effect which is consistent with that found previously.[40]

Upon further examination, walking path quality was significantly correlated with several NSA variables (% high school education, % below poverty level, median household income) and knowledge of the items used to create incivility suggests that walking path quality in this analysis may be a proxy for the general socioeconomic condition of the neighborhood. This is not a surprising result since the paths to school geographically slice through NSAs and the corresponding walking path

Table 3 Multilevel, Multivariate GEE Model Odds Ratios, 95% Confidence Intervals (CI) and *P*-Values for Child Reported Walking to School Controlling for Clustering by Neighborhood Statistical Area (NSA)

Variable	Odds ratio	95% CI	Wald P-Value†
Individual child variables			
Male	1.20	0.71–2.04	0.49
Age in months (centered)	1.01	0.99–1.04	0.19
African American	0.75	0.38–1.47	0.40
Reduced meals	2.23	1.03–4.81	**0.041**
Free lunch	1.54	0.69–3.47	0.29
Individual parent variables			
Is neighborhood safe?	3.00	1.70–5.29	**0.0001**
Some college	0.75	0.46–1.23	0.25
College or higher	1.06	0.35–3.19	0.91
Annual income $5000–$9999	2.59	0.63–10.71	0.19
Annual income $10,000–$19,999	0.73	0.34–1.58	0.43
Annual income $20,000–$29,999	0.63	0.32–1.24	0.18
Annual income $30,000–$49,999	0.63	0.32–1.26	0.19
Annual income $50,000–$99,999	0.57	0.27–1.22	0.15
Annual income > $100,000	0.15	0.03–0.85	**0.032**
Walking environment variables			
Walking path length (500 ft)	0.95	0.92–0.97	**0.0001***
Walking path quality (per 100 ft)	0.88	0.72–1.07	0.19
Incivility for home street block	1.10	1.03–1.19	**0.007**
Neighborhood level variables			
NSA—median income ($1000)	1.03	1.00–1.06	**0.038**
NSA—% below poverty level	1.02	0.97–1.07	0.37
NSA—% > high school education	0.96	0.89–1.03	0.21
School 2	0.68	0.34–1.36	0.28
School 3	0.88	0.40–1.94	0.74
School 4	0.11	0.04–0.30	**0.0001***
School 5	0.66	0.20–2.18	0.50
School 6	0.52	0.18–1.50	0.22

† Values in bold are significant at α = .05.

* Indicates P < 0.0001.

quality variable averages the included incivilities. Since the NSA level variables account for socioeconomic status, models which include these factors and further adjust for clustering at the NSA level may contribute to the statistically nonsignificant finding of the walking path quality effect.

Conclusion

The methodology presented in this paper addresses a gap in the literature by combining an objective observational instrument with spatial statistics and GIS to produce a measure that is reproducible, can be tailored to focus on specific environmental domains, and be calculated for every street block in the study region. Since the underlying data are based on a detailed objective audit, reproducing and comparing results for multiple studies is much simpler than comparing results based on GIS-derived objective measures, which are often unstandardized and unvalidated. In addition, measures based on objective audits can be much more detailed and focused on relevant environmental domains or features than those found in GIS databases. Finally, by taking advantage of tools from the field of spatial statistics (as demonstrated here using spatial prediction), objective values can be estimated for every block without the need to conduct an audit of each one. Spatially referenced data are available in almost every study of physical activity and environment, but explicit use of spatial statistics has been limited. In fact, a systematic review published by Wong and colleagues discussed how the current body of literature on the built environment and active transport to school has been characterized by inconsistent measures of spatial concepts, which has limited the ability to develop programs and policies informed by the evidence.[41]

This research expanded on prior studies in the extant literature by accounting for not only the environment surrounding participants' homes and/or their schools, but also the environment between home and school via along identified paths to school. Few existing studies have focused on the quality of the path. A study by Zhu and Lee[4] of children walking to school in Austin, Texas measured the quality of some physical factors along the route to school such as the presence of trees for shading, cleanliness, and lighting. Although this study asked about safety, as is the case for similar studies in the published literature, barriers relating to broader incivilities were not assessed. In our study, we explored incivility using a validated objectively measured tool, which also was an extension of prior studies in this area.

Although the walking path quality variable used, defined as the average incivility along these identified paths, was not statistically significantly associated with walking to school status in this sample, some noteworthy findings deserve emphasis. The estimated effect of walking path quality in the final multivariate regression model was in the direction supporting our hypothesis that higher incivilities along a path to school are associated with less likelihood of walking to school. On the contrary, the effect for just the home street block incivility suggests the counter intuitive opposing effect that was also supported in our prior research.[40] As mentioned though this could be due to the limited family and community resources in an urban public school setting; most students have to walk out of necessity.[40] Thus environmental hazards may have minimal effect on the likelihood that a child will walk to school. Further examination of the items used to create the incivility and recognizing that the identified walking to school paths geographically slice through NSAs, suggests that walking path quality in this analysis may be a proxy for the general socioeconomic condition of the neighborhood. Since the NSA level variables account for socioeconomic status, models that include these factors and further adjust for clustering at the NSA level may contribute to the statistically nonsignificant finding of the walking path quality effect. However, this only goes to further support our hypothesis that it is more than just the environment immediately surrounding one's home but rather information on the environment between home and school that might prove a determinant for walking to school.

The significance of parent perception of neighborhood safety highlights the importance of parent attitudes on walking to school while the significance of school 4 suggests there may be unmeasured school level variables, which make walking to this school particularly unlikely. There is somewhat conflicting evidence regarding income with increasing NSA median income associated with higher odds of walking and parent annual income of more than \$100,000 associated with lower odds of walking. In essence, higher income households may have greater resources at their disposal (eg, personal automobiles, flexible work schedules) to enable them to provide transportation for their children to and from school. While this analysis does corroborate overall trends in the literature, a more sophisticated study is needed to unravel the complex associations and interactions affecting walking to school.

There are several limitations in the data and models used to estimate incivilities, determine walking path quality, and model walking to school. A limitation of using the NIfETy and MORE Project data sets for this project is that neither of these studies was explicitly designed to measure walking to school and potentially important variables are missing from each data set. For the NIfETy data, variables related to the built environment such as sidewalk presence, land use, aesthetics, and street scale were either not collected or are measured imprecisely. The MORE Project was primarily focused on the impact of chronic community violence and did not collect potentially important individual level walking variables such as car ownership, school policies and climate related to walking/busing, or parental attitudes toward walking. In addition, this study did not collect objective measures of walking to school and was therefore limited by its reliance on self-reported accounts of walk to school behavior. There has been some success utilizing GPS units to derive the actual path of travel and this methodology should be explored further.[64-65]

Another limitation involves the incivility score which is a simple summated scale of "negative" NIfETy items. The actual attractiveness of a street block for walking is likely more impacted by some factors than others (eg, unboarded abandoned buildings vs. cigarette butts) and it is therefore unclear that blocks with the same incivility value offer equivalent walking experiences. In addition there is no measure of physical and social features such as landscaping and positive adult interactions which may serve to encourage walking and mitigate the effects of block incivilities.

Other limitations involve the walking path quality variable. When calculating walking path quality only the shortest road-based route from home to school was considered. However, the true path could deviate significantly from the shortest road-based path and may itself depend on the path quality. For example a child may take a longer path specifically to avoid blocks with high incivilities. For instance, ad hoc field observations revealed that when walking to and from schools, children sometimes cut across fields or through alleys, which raises questions about the paths that we presupposed that they travel along. If the GIS determined shortest path traveled through the higher incivility blocks for this child, the effect of path quality on the decision to walk to school would be inaccurate. In addition, average incivility along the path was used although 2 paths with the same average incivility could represent very different walking experiences (all moderate vs. very high and very low).

There are also some limitations for the models used in the walking to school analysis. These models did not account for the uncertainty of predicted incivility values[66] or the imputed socioeconomic variables for some parents.[67] In addition, only cross-sectional data were used so determining causation is not possible. There exists the possibility of self-selection bias with parents who are more reliant on walking (eg, do not own personal vehicles or drive) specifically choosing to live in neighborhoods where their children can easily walk to school.

These results suggest some areas for future research. Measures of the walking environment such as walking path quality could benefit by incorporating additional data such as positive factors which facilitate physical activity or GIS-derived data such as street size, traffic volume and speed, sidewalks, lighting, and green space. For GIS variables, issues related to lack of standardization, inconsistent availability, and unvalidated measurement need to be considered. In addition, factor analysis of objective audit items could identify specific domains of importance and factor scores from such analysis used to weight important features more heavily.[68] Structural equation modeling could also be beneficial in conceptualizing and exploring the relationship between walking environment and other factors specified in the ecological model for physical activity framework.[69]

For walking path quality, measures other than the average value should be considered. These measures could be other single number summaries such as the median walking path quality or the maximum incivility encountered along a path. More complex measures could consider the percentage of high, low and moderate incivility blocks or the order in which blocks of varying incivility value were encountered. Another important extension for walking path quality involves accounting for uncertainty of the exact path of travel. Possible extensions include using a GIS buffer around the shortest path and including all paths within the buffer as potential routes to school. A similar idea is to calculate all potential paths under a predetermined length between home and school. The potential paths could then be weighted according to their path quality and other features such as directness and number of street crossings.

The development of a sound measure and metric for assessing path quality has implications for research, policy and practice. A more complete accounting of the built environment would provide the opportunity to use path quality indices for a host of behaviors, and free researchers across multiple fields from collecting original data each time a new location, environment, or path was studied. Policies focused on the environmental changes are often more successful and less costly than policies focused on behavior change[70]. And in particular, with regard to youth, evidence supporting a rigorous objectively-derived path-quality measure could mobilize non-school-based constituents (and attendant resources) to improve school path quality because paths to school cross communities and businesses, entities from where resources could be leveraged and action-oriented partnerships developed.

In summary, these results indicate that urban children living in communities characterized by the highest physical and social disorder are the most likely to walk to school, potentially placing them at risk for adverse health outcomes. The methodology developed here addresses a gap in the literature by combining an objective audit instrument with spatial statistics and GIS to lay the groundwork for practical and rigorous measures that will help us better understand the influence of physical and social disorder on walking to school.

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