


SUPPLEMENT ARTICLE

Traffic-related environmental factors and childhood obesity: A systematic review and meta-analysis

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Summary

A growing body of research links traffic-related environmental factors to childhood obesity; however, the evidence is still inconclusive. This review aims to fill this important research gap by systematically reviewing existing research on the relationship between traffic-related environmental factors and childhood obesity. Based on the inclusion criteria, 39 studies are selected with environmental factors of interest, including traffic flow, traffic pollution, traffic noise, and traffic safety. Weight-related behaviours include active travel/transport, physical activity (PA), and intake of a high trans-fat diet or stress symptoms; weight-related outcomes are mainly body mass

Zhuo Wang and Li Zhao contributed equally to this work.

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index (BMI) or BMI z-scores and overweight/obesity. Of 16 studies of weight-related behaviours, significant associations are reported in 11 out of 12 studies on traffic flow (two positively and nine negatively associated with PA), five out of six studies on traffic safety (four positively and one negatively associated with PA), one study on traffic pollution (positively with unhealthy food consumption), and one study on traffic noise (negatively associated with PA). Among 23 studies of weight-related outcomes, significant associations are reported in six out of 14 studies on traffic flow (five positively and one negatively associated with obesity outcome), seven out of 10 studies on traffic pollution (all positively associated with obesity outcome), and two out of five on traffic noise (all positively associated with obesity outcome). Our findings show that long-term traffic pollution is weakly positively associated with children's BMI growth, and traffic flow, pollution, and noise could affect weight-related behaviours. Associations between traffic density and noise and weight status are rather inconclusive.

KEYWORDS

air pollution, obesity, physical environment, traffic

1 | INTRODUCTION

Childhood obesity is one of the most serious public health challenges in both high-income and low- and middle-income countries (LMICs) with rapid economic growth.^{1,2} The prevalence has increased at an alarming rate especially in some LMICs while the rate of increase has slowed down in some high income countries.³⁻⁵ The total amount of children under five with overweight and obesity has risen from 32 million in 1990 to 41 million in 2016 globally and is projected to nearly double, reaching 70 million by 2025.^{6,7} Without interventions, childhood obesity will likely continue into adolescence and adulthood⁸ and develop a variety of physical health problems at younger age, such as diabetes, cardiovascular disease, non-alcoholic fatty liver disease, musculoskeletal disorders, some cancers, and disability, as well as other psychological health issues against social and emotional well-being (eg, self-esteem).^{9,10} The mechanism of obesity development has not been fully understood. It is thought to be caused by multiple factors, such as genes, sugary beverages, snack foods, sedentary behaviours, environmental factors, sociocultural factors, family factors, and psychological factors.¹¹⁻¹⁷ As previous studies have shown limited effect of behavioural interventions in preventing childhood obesity,¹⁸ increasing attention is now being paid to environmental determinants.^{19,20}

Of numerous environmental determinants, traffic-related environmental factors, such as air and noise pollution, were found to have a dominant influence on children's health since the early 20th century. Following the rapid urbanization and rising per capita income, private motor vehicle ownership has been increasing fast, especially in LMICs.²¹⁻²³ Traffic accidents are eighth leading cause of death globally, and road traffic injuries are now the leading cause of death among people aged 5 to 29 years.²⁴ Fear of traffic is a commonly reported barrier to outdoor physical activity (PA), which is linked to

children's PA and obesity. A growing body of research has also shown that increasing traffic density in urban areas has caused multiple problems, such as noise, air pollution, and other environmental issues that can affect children's psychology, sleep, endocrine, exercises, etc, which are all linked to childhood obesity.^{25,26} For example, Kim et al²⁷ reported that higher exposure to near-roadway air pollution in early life was associated with a faster increase in body mass index (BMI) growth, subsequently leading to a higher BMI at age 10 years. Jerrett et al²⁸ showed that traffic densities were positively associated with BMI in young adults aged 18 years old. Yet, some other studies have shown no significant associations between traffic-related factors and childhood obesity. For example, Weyde et al²⁹ reported that the development of BMI was not related to exposure to road traffic noise in a longitudinal study tracking subjects from birth to 8 years old. To our best knowledge, there has not been any systematic review or meta-analysis on this important topic.

To fill this gap, we conducted a systematic review and meta-analysis on the association between traffic-related factors and childhood obesity. For the first time, this study provides a comprehensive summary of associations between a variety of traffic-related factors and children's obesity-related behaviours and outcomes. As mounting evidence suggests enduring effects of early-life environmental exposures on obesity development,³⁰ it is necessary to draw attention on the health implications of rapidly growing traffic intensity, especially its influence on the development of obesity in early childhood and increased risk of metabolic disease in later life.

2 | METHODS

Following the guideline from the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA), we conducted the systematic review and meta-analysis based on the most robust

evidence on the relationship between traffic-related factors and childhood obesity.

2.1 | Search strategy

We conducted a keyword search in four electronic bibliographic databases (Cochrane Library, PubMed, Web of Science, and Embase) for all studies published prior to January 1, 2019, and searched all possible combinations of three groups of keywords related to traffic, children, and weight-related behaviours and/or outcomes (eg, diet, PA, and adiposity measures) (Data S1).

We also supplemented the database search with manual review of the reference lists of the included articles, relevant review articles, and expert suggestions. Duplicate documents were deleted before the screening process. Two reviewers (Z.W. and Q.H.) independently screened all titles and abstracts, and full texts at different stages, for excluding irrelevant documents. Any disagreement between the two reviewers was reconciled by a third member who was not involved in the initial assessment (L.Z.). The whole process is shown in Figure 1.

2.2 | Study selection

>All of the following criteria needed to be met for the review:
(a) participants: children and adolescents (age less than 18);

(b) study outcomes: weight-related behaviours (e.g., dietary intake, PA, and sedentary lifestyle) and/or outcomes (e.g., overweight and/or obesity, BMI index and/or z-score, waist circumference, waist-to-hip ratio, and body fat); (c) exposure variables: traffic-related environmental factors; (d) study designs: longitudinal studies including prospective and retrospective cohort studies, cross-sectional studies, and randomized controlled trials (RCTs); (e) type of articles: peer-reviewed publications excluding letters, editorials, protocols, or review articles; (f) time of publication: before January 1, 2019; and (g) language: only in English.

2.3 | Data extraction and preparation

For the selected studies, we collected key information, including author name, publication year, study area, scale, and design, sample size and age, sampling characteristics (follow-up years, number of repeated measures, attrition rate), statistical models, measures of traffic-related variables, other adjusting covariates in the analysis, measures of body-weight status, and key findings on the association between traffic-related factors and weight-related behaviours/outcomes. Two reviewers (Z.W. and Q.H.) independently extracted data from each included study, with discrepancies resolved by a third reviewer (L.Z.).

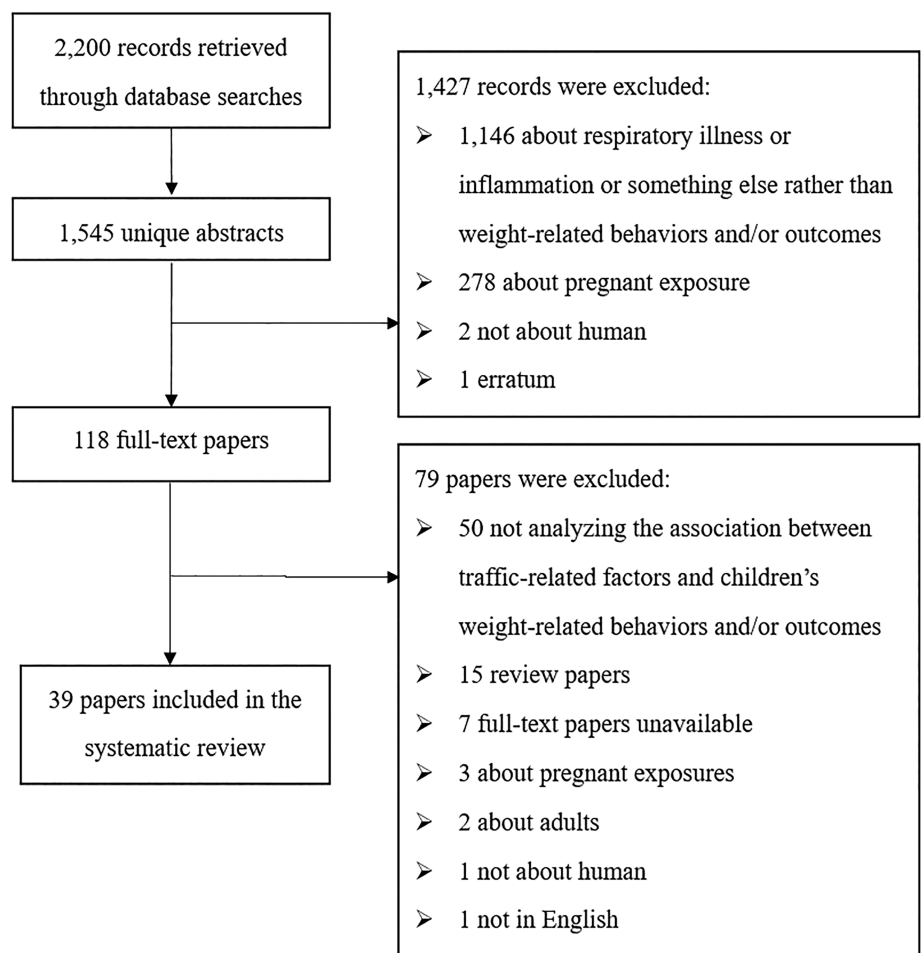


FIGURE 1 Study exclusion and inclusion flowchart

2.4 | Study quality assessment

National Institutes of Health's Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies was used to assess the quality of each selected study. Based on 14 criteria, each study was graded (Table S4). For each criterion, one point was marked if the answer was "yes"; otherwise, zero point was assigned (i.e., the response was "no," "not applicable," "not reported," or "cannot determine"). We obtained a study-specific global score ranging from zero to 14 by summing up the scores across all criteria (Table S1). This assessment tool was used to assess the strength of scientific evidence, not as criteria for exclusion.

2.5 | Meta-analysis

We conducted separate analyses according to different study designs, traffic-related factors, and weight-related behaviours/outcomes. For analysis of the cohort studies, a basic inverse variance method was used for pooling.³¹ We examined heterogeneity among studies with I^2 statistic and conducted a sensitivity analysis by using statistical models regarding heterogeneity (random vs fixed effects). In the analysis of other types of studies except longitudinal studies, we generally described and summarized the data. All data were analysed with R 3.6.0 software, and the results of meta-analysis were visualised using forest plots.

3 | RESULTS

3.1 | Study selection

Thirty-nine studies were finally included in our review (Figure 1). The initial search identified 2200 articles, including 443 abstracts from PubMed, 23 abstracts from Cochrane Library, 538 abstracts from EmBase, and 1196 articles from Web of Science. After excluding duplicate abstracts, 1545 unique titles and abstracts were reviewed and 1427 articles were further excluded. The full texts of the remaining 118 articles were reviewed against the study selection criteria. Of these, 79 articles were further excluded. Therefore, 39 studies that met our inclusion criteria were brought into the final article-pool included in the review.

3.2 | Study characteristics

The final thirty-nine studies were conducted in 18 countries: 17 in the United States, five in Australia, four in Germany, three in Italy, two in each of China, the Netherlands, and Sweden, and one in each of Belgium, Canada, Danish, France, Hungary, Japan, Malaysia, Norwegian, Spain, Switzerland, and the United Kingdom (Table 1). There were five national-level, 10 state/province-level, and 24 city-level studies. Eighteen were longitudinal studies and 19 were cross-sectional studies,

with sample sizes ranging from 300 to five million. Twenty studies included participants aged under six; 18 studies included the ages 6 to 12; and 10 studies included the ages 13 to 18. One RCT study focused on middle school students mean aged 13.7, and one qualitative study focused on 13 caregivers of preschoolers aged 0 to 4.

3.3 | Measures of the traffic-related factors

Traffic-related factors in the included studies were mainly traffic flow, traffic pollution, traffic noise, and traffic safety (Table S1). There were 26 out of 39 studies (67%) using traffic flow as the independent variable. Among them, 10 studies collected the perceived exposure to traffic flow using questionnaires answered by parents or children, recorded as a categorical variable; four studies used the length of roads as indicators for traffic flow, and 10 studies used annual average daily traffic (AADT) or traffic density (i.e., AADT multiplied by the length of roads); two were density of intersections or stops to capture traffic densities. Eleven out of 39 studies (28%) had traffic-related air pollution as the independent variable, among which 10 used traffic exhausts and particulates (e.g., sulfide and PM_{2.5}), and one used a perceived measure of exposure to traffic-related air pollutants. There were six studies (15%) with traffic noise as the independent variable, of which five studies were expressed as the daily average noise exposure in decibel, and one study as the parental perception of exposure to traffic noise. Six studies (15%) involved traffic safety, one for injury rate, and five for perceived safety.

3.4 | Associations between traffic-related factors and weight-related behaviours

Sixteen out of 39 studies (41%) involved weight-related behaviours as the outcome variable: Five studies focused on the degree of active travel/transport (13%); nine studies examined physical activity outcomes (23%); and others were about intake of a high trans-fat diet or stress symptoms (5%). Meanwhile, the significant results accounted for 94% of the selected articles (Tables S2 and S3). Twelve studies were about the relationship between traffic flow (five were the perceived exposure or categorical variables collected by questionnaires; seven were continuous variables about intersections/stop density, traffic density, or road length) and behaviours (five were PA [h/wk] or step counts; seven were levels of walking/biking). Of these studies, one study showed that speeding traffic reduced children's PA using qualitative methods⁵³; one showed that children with high levels of walking were more likely to perceive heavy traffic³³; eight studies showed that more traffic flow was associated with less PA; one showed that average annual daily traffic was irrelevant to children's activity³⁹; and one showed that density of street intersections was positively associated with rates of active travel.³⁶

Six studies examined the relationship between traffic safety and PA.^{33,35,41,45,56,64} One showed that children with higher levels of walking were more likely to perceive streets as unsafe,³³ and one

TABLE 1 Basic characteristics of 39 included studies (see references in the main text)

Reference (First Author)	Study Area (Scale) ^a	Sample Size	Age at Baseline, y	Study Design ^b	Sample Characteristics (Follow-up Years; Number of Repeated Measures; Attrition Rate) ^c	Statistical Model
Alderete (2017) ³²	Urban Los Angeles, CA, USA (C)	314	Aged 8-15 (2001-2012), mean \pm SD (11.3 \pm 1.7)	L	Recruited in two waves from 2001 to 2012 and followed for an average of 3.4 years (SD 3.1), providing up to 1253 total observations; each annual visit; 96% retention (314/328).	Linear mixed-effects models
Alton (2007) ³³	Birmingham, UK (C)	473	9-11	C	Six primary schools, range of socio-economic classifications including 250 (52.9%) boys and 160 (33.8%) from ethnic minority populations; 82% response rate.	Binary logistic regression
Bloemsa (2018) ³⁴	Three different regions (north, central and west) of the Netherlands (N)	3680	Aged 3 (2.5 to 3.5) (baseline study population consisted of 3963 children born in 1996-1997)	L	Followed from the age of three years until the age of 17 years; data collected by questionnaires during pregnancy, at the child's ages of 3 months and 1 year, and yearly thereafter until the child was 8, 11, 14, and 17 years old; 48% retention until 17 age group (1767/3680).	Generalized linear mixed models
Bringolf-Isler (2010) ³⁵	Berne, Biel-Bienne, and Payerne, in Switzerland (C)	1345	6/7, 9/10, and 13/14 (in 2004-2005)	C	The children, of age 6/7, 9/10, and 13/14 years, were living in Berne (German speaking), Biel-Bienne (German/French speaking), and Payerne (French-speaking); 65% were included.	Linear regression models
Bungum (2009) ³⁶	Northern Utah community, USA (C)	2692	15.18 (mean)	C	Data were collected from students who attended one of two junior highs, or one of two high schools in a northern Utah community.	Logistic regression
Chen (2018) ³⁷	12 Southern California communities, USA (C)	3100	Fourth and seventh grades (1993-1994)	L	4- to 8-year follow-up; Annual dietary information was collected; 58% retention (3100/5321).	Generalized linear mixed-effects models
Christensen (2016) ³⁸	Danish (N)	40 974	Singletons at birth based on the Danish National Birth Cohort (in 1996)	L	7-year follow-up; The mothers were interviewed during pregnancy around week 16 and 30, and when the child was 6 months and 18-month old, and during the month of the child's 7-year birthday.	Multiple linear regression and logistic regression models

(Continues)

TABLE 1 (Continued)

Reference (First Author)	Study Area (Scale) ^a	Sample Size	Age at Baseline, y	Study Design ^b	Sample Characteristics (Follow-up Years; Number of Repeated Measures, Attrition Rate) ^c	Statistical Model
Cradock (2009) ³⁹	Four communities in the Boston metropolitan area, USA (C)	152	13.7 (mean, in 1997)	R	The study design matched schools on enrolment size and ethnic composition. A stratified random sample of 256 students participated in a substudy that collected objectively monitored physical activity data in 1997; 59% were included (152/256).	Linear mixed models
Crawford (2010) ⁴⁰	19 state primary schools in high (n = 10) and low (n = 9) socio-economic areas in Melbourne, Australia (C)	314	10-12 (in 2001)	L	5-year follow-up from 2001 to 2006; three time points; 34% retention (314/926).	Generalized estimating equations
de Vries (2007) ⁴¹	Six cities, Netherlands (C)	422	6-11 (2004-2005)	C	Children aged 6 to 11 years living in the selected neighborhoods was recruited from 20 elementary schools (two schools per neighbourhood); 34% were included (422/1228).	Univariate and multivariate linear regression analyses
Dong (2014) ⁴²	25 districts in seven cities from Liaoning Province in Northeast China (S)	30 056	2-14 (in 2009)	C	Randomly selected one elementary school and two kindergartens in April 2009, from each of the 25 districts in seven cities.	Two-level logistic model
Duncan (2014) ⁴³	Massachusetts, USA (S)	49 770 for cross-sectional analyses; 46 813 for longitudinal analyses	4-18 (2011-2012)	L	4-year relationships from the earliest available (2008-2011) to the most recent (2011-2012) visit; for cross-sectional analyses at least one BMI z-score was available from a well-child visit between August 2011 and August 2012; for longitudinal analyses at least two BMI measures between January 2008 and August 2012.	Spearman correlations; Multivariable models
Dunton (2012) ⁴⁴	San Bernardino County, California, USA (C)	121	9-13 (2009)	L	1-year follow-up; data were collected twice.	Multilevel logistic regression, Generalized Estimating Equations (GEE) regression

(Continues)

TABLE 1 (Continued)

Reference (First Author)	Study Area (Scale) ^a	Sample Size	Age at Baseline, y	Study Design ^b	Sample Characteristics (Follow-up Years; Number of Repeated Measures, Attrition Rate) ^c	Statistical Model
Esteban-Cornejo (2016) ⁴⁵	Baltimore, MD–Washington, DC, and Seattle–King County, WA, USA (C)	928	12–16 (2009–2011)	C	The sampling was designed to be balanced by age and sex and to approximate the ethnic distribution of the regions; The participation rate was 36% and did not vary significantly by quadrant.	Mixed-effects linear regression
Evans (2001) ⁴⁶	The lower Inn Valley of Tyrol, Austria (C)	115	10	C	The sample consists of 115 children in grade 4 who were selected from a large, representative sample of children.	Linear regression
Fioravanti (2018) ⁴⁷	Rome, Italy (C)	719	Newborns were enrolled at birth (2003–2004)	L	8-year follow-up; questionnaires were conducted at child's birth, 6 months, 15 months, 4, 7, and 8 years. Measures of BMI were collected at 4 and 8 years during clinical examinations, while data on abdominal fat and blood lipids were collected only at the 8-year follow-up; 69.4% retention (499/719).	Logistic regression models, Generalized Estimating Equation models (GEE) and linear regression models
Gose (2013) ⁴⁸	Kiel (North Germany), Germany (C)	485	Average age 6.1 (5.8–6.4; between 2006 and 2008)	L	4-year relationships; anthropometric measurements were conducted at baseline and follow-up.	Generalized estimating equations (GEE)
Grassi (2016) ⁴⁹	Five cities in Italy (N)	1164	Aged 6–8 (2014–2015)	C	Randomly recruited children attending primary school in five Italian cities: Brescia, Lecce, Perugia, Pisa, and Torino.	Binomial logistic regression
Gustat (2015) ⁵⁰	Louisiana, USA (S)	844	From PK through eighth grade (2009)	C	Participants included a total of 844 parents of students from the selected SRTS project schools. The parent surveys had return rates of 32% to 46% over the 5 schools.	Logistic regression
Hinojosa (2018) ⁵¹	California, United States (S)	5 265 265	Grades 5, 7, and 9 of state's public schools (2003–2007)	C	The data are considered repeated cross-sections as data from the same student are not identifiable over time due to student ID suppression in the data.	Machine learning (Random Forest) and multilevel random effects model

(Continues)

TABLE 1 (Continued)

Reference (First Author)	Study Area (Scale) ^a	Sample Size	Age at Baseline, y	Study Design ^b	Sample Characteristics (Follow-up Years; Number of Repeated Measures, Attrition Rate) ^c	Statistical Model
Huang (2018) ⁵²	Hong Kong, China (S)	8298	0-2 and 2-8 (during 1997-2005)	L	15-year follow-up from birth to 8 years; BMI values collected at 9, 11, 13, and 15 years; 55% retention (4577/8298).	Linear regression and partial least squares (PLS) regression
Jarrett (2013) ⁵³	Low-income community in Chicago, USA (C)	13	preschoolers	Q	An interpretive approach was adopted to capture the daily lived experiences of participants and the meanings that women gave to those experiences.	Qualitative methodologies
Jerrett (2010) ²⁸	11 communities in Southern California, US (S)	2889	9-10 (in 1993 and 1996)	L	8-year follow-up from 1993 and 1996 when children was enrolled to the age 18 or high school graduation; annual height and weight measurements; 87% retention (2889/3318).	Multi-level growth curve model
Jerrett (2014) ²⁵	13 communities across Southern California, USA (S)	4550	5-11 (2002-2003)	L	4-year follow-up from attending kindergarten and first grade during the 2002-2003, annually measured	Dispersion models and Multilevel model
Kim (2018) ²⁷	13 Southern California communities, United States (S)	2318	Kindergarten and first grade, average 6.5 years, SD = 0.7 (2002 to 2003)	L	4-year follow-up; annual visits.	Linear mixed effects models
Lange (2011) ⁵⁴	28 different residential districts of the city of Kiel (North Germany), Germany (C)	3440	13-15 (48.7% boys; in 2004 and 2008)	C	Cross-sectional data from the Kiel Obesity Prevention Study collected between April 2004 and August 2008.	Linear and logistic multilevel regression analyses
Larsen (2012) ⁵⁵	London, Ontario, Canada (C)	614	grades 7 and 8 students	C	Grade 7 and 8 students (n = 614) from 21 schools throughout London, Ontario, participated in a school-based travel mode survey; response rate was 49% (810/1666), final sample were 614 students.	Logistic regression
Lovasi (2011) ⁵⁶	New York City, USA (C)	428	2-5 (in 2003-2005)	C	This study included 428 Head Start enrollees, ages 2-5 years, with interview, accelerometry, and anthropometry data.	Generalized estimating equations

(Continues)

TABLE 1 (Continued)

Reference (First Author)	Study Area (Scale) ^a	Sample Size	Age at Baseline, y	Study Design ^b	Sample Characteristics (Follow-up Years; Number of Repeated Measures, Attrition Rate) ^c	Statistical Model
McConnell (2015) ⁵⁷	12 communities in Southern California, USA (S)	3318	Aged 10 (in 1993 and 1996)	L	8-year follow-up of two cohorts in which fourth grade classrooms were recruited in 1993 and 1996; annually BMI measured (average [\pm SD] 6.4 \pm 2.4 BMI measurements.); Subsequent attrition was 5%-10% per year.	Multilevel model
McTigue (2015) ⁵⁸	USA (N)	2295	Average age 11.2 [1.3] (mean [SE]; 2004-2005)	L	Over 6-year follow-up from 2004-2005 to 2014; six annual assessments; 89%-96% of girls completed each study assessment.	Linear mixed-effects modelling
Sakai (2013) ⁵⁹	Japan (N)	695 600	72 380 kindergartners aged 5 years; 270 720 elementary school children aged 6 to 11 years; 225 600 junior high school students aged 12 to 14 years; 126 900 high school students aged 15 to 17 years (in 2008)	C	The data were collected annually by sampling with probability proportionate to size. These samples corresponded to 4.7% of all children and adolescents in Japan in 2008.	Generalized linear regressions
Schüle (2016) ⁶⁰	Munich, Germany (S)	3499	Aged 5-7 (2004-2007)	C	Considering children (53% boys and 47% girls) taking part in the obligatory school entrance health examination, data were pooled from three surveys between 2004 and 2007 from 18 school enrolment zones in Munich.	Hierarchical logistic regression models.
Su (2013) ⁶¹	10 Southern California Children's Health Study (CHS) communities, USA (C)	4338	5-7 (2002-2003)	C	Students in participating schools were enrolled in kindergarten or first grade; Questionnaires were completed and returned from 65% eligible children, leaving 4338 participants in the 10 communities for analysis.	Logistic regression and mixed regression
Timperio (2005) ⁶²	Melbourne, Australia (C)	1210	291 families of 5-6 years and 919 families of 10-12 years children (in 2001)	C	19 state primary schools in high (n = 10) and low (n = 9) socio-economic areas in Melbourne.	Logistic regression analyses and Unadjusted logistic regression analyses

(Continues)

TABLE 1 (Continued)

Reference (First Author)	Study Area (Scale) ^a	Sample Size	Age at Baseline, y	Study Design ^b	Sample Characteristics (Follow-up Years; Number of Repeated Measures, Attrition Rate) ^c	Statistical Model
Timperio (2010) ⁶³	19 state elementary schools in Melbourne, Australia (C)	409	140 5-6 years old and 269 10- to 12-year-old children (in 2001)	L	3-year follow-up from 2001 to 2004 (2.9 ± 0.4 years); measured at the child's school at baseline and at the child's school or home at follow-up.	Univariate and multivariable linear regression analyses
Tung (2016) ⁶⁴	Klang, Selangor, Malaysia (C)	250	9-12	C	The respondents were recruited using a multistage sampling method, whereby six schools were randomly selected from a list of 50 primary schools that fulfilled the inclusion criteria of being multi-ethnic and coeducational in composition; response rate was 41.6% (250/600).	Multiple linear regression
Vanhelst (2013) ⁶⁵	10 European cities: Vienna (Austria), Ghent (Belgium), Lille (France), Athens (Greece), Heraklion (Greece), Pecs (Hungary), Rome (Italy), Dortmund (Germany), Zaragoza (Spain), and Stockholm and Stockholm (Sweden) (C)	3528	12.5-17.5 (2006-2007)	C	Data from a random sample of European adolescents aged 12.5-17.5 years. In total, 3528 adolescents (1844 girls and 1684 boys) meeting the inclusion criteria completed all examinations.	Linear regression
Wallas (2018) ⁶⁶	Stockholm County, Sweden (C)	4089	Newborns were enrolled at birth (1994-1996)	L	16-year follow-up; repeated questionnaires, clinical examinations, and biological sampling from born to age 16 (for example: BMI collected at 6, 12, and 18 months, 2, 3, 4, and 5 years, and 7, 10, 12, and 16); response rates for the questionnaire were 76% for children.	Logistic- and quantile regression models
Weyde (2018) ²⁹	Oslo, Norwegian (C)	6403	Newborns were enrolled at birth (2000-2009)	L	8-year follow-up from born to 8 years; BMI values collected at birth, 18 months and 3, 5, 7, and 8 years.	Linear mixed models

showed that the level of safe walking had no connection with children's PA.⁴¹ Three studies showed that more traffic safety was associated with more activity,^{35,45,64} and one showed that higher injury rates were associated with lower activity counts.⁵⁶ Another study suggested that exposure to traffic-related air pollutants was associated with an increased consumption of trans-fat and fast foods among adolescents, and children in noisier neighborhoods rated higher in perceived stress symptoms, with diminished motivation for a given task among girls.^{37,46}

3.5 | Associations between traffic flow and obesity outcomes

Regarding the measure of weight-related outcomes, six studies used overweight/obesity (15%), eight studies used the BMI or BMI z-scores (21%) in examining the association between traffic flow and obesity outcomes, and the significant results accounted for 43% (Tables S2 and S3). We combined two longitudinal cohort studies with meta-analysis conducted by the same author in similar locations but different years and different populations.^{25,28} The dependent and independent variables were all continuous variables (annual average daily traffic volumes (AADT) and children BMI). Each of the results showed that AADT were positively correlated with BMI, and the meta-analysis of the pooled sample with 7439 participants showed a marginal correlation (Figure 2).

Of the other 12 studies, three cross-sectional studies used both dichotomous independent (parental perception of children's exposure to traffic) and dependent variables (overweight/obesity), showing one positive and two irrelevant associations between parental perception of exposure to traffic volume and children's weight status in their living environment.^{49,60,62} We also pooled these three studies and found there was no statistically significant correlation between the two variables (OR = 1.16; 95% CI, 0.87-1.55; $I^2 = 58%$). The other three studies focused on the association between the total length of roads in neighbourhood and children's weight status, of which one presented negative and two showed no association.^{40,59,63} The rest of the six

studies showed two positive and four irrelevant association between daily traffic volumes, traffic density or parental perception measure and children's weight status.

3.6 | Associations between traffic pollution and obesity outcomes

Four studies used overweight/obesity (10%), six studies used BMI or BMI related index (15%) as dependent variables in examining the relationship between traffic pollution and obesity outcomes, and the significant results accounted for 70% (Tables S2 and S3). Ten studies examined the association between air pollution exposure which was closely related to traffic emissions such as nitrogen oxides (NO_x) and PM_{2.5} and children's weight status: seven reported a positive association; two reported no association; and one reported no association between parental perception of children's exposure to air pollution and childhood obesity.

Three longitudinal cohort studies reported nitrogen oxides (NO_x) exposure led to an increase in children's BMI growth (the rate of growth during the follow-up period), and the meta-analysis including 10 163 participants showed that there was a trivial significant increase in children's BMI growth ($\beta = 0.05$; 95% CI, 0.00-0.10), with considerable heterogeneity ($I^2 = 89%$) (Figure 3).^{25,27,57} Two longitudinal cohort studies examined the correlation between nitrogen oxides (NO_x) levels and overweight/obesity, one of which defined overweight/obesity according to age and sex-specific International Obesity Task Force (IOTF) cut-offs.^{34,47} A pooled analysis of the two studies showed no statistically significant correlation with considerable heterogeneity ($I^2 = 86%$).

3.7 | Associations between traffic noise and obesity outcomes

Two studies used overweight/obesity (5%), three studies used BMI or BMI related index (8%) as dependent variables in assessing the relationship between traffic pollution and obesity outcomes, and the

FIGURE 2 Summary of random-effects meta-analyses of longitudinal cohort study reports of effect of annual average daily traffic (AADT) to children body mass index (BMI)

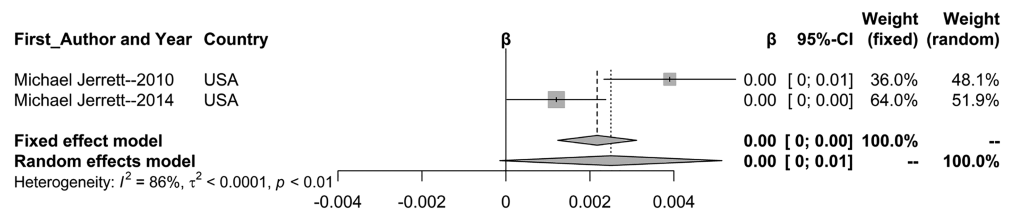
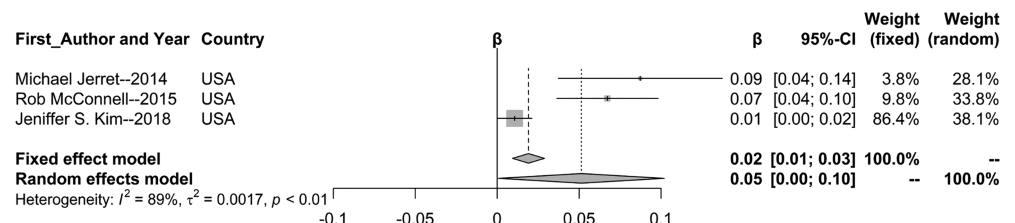


FIGURE 3 Summary of random-effects meta-analyses of longitudinal cohort study of effect of nitrogen oxides (NO_x) exposure to children body mass index (BMI) growth



significant results accounted for 40% (Tables S2 and S3). Four studies examined the association between traffic noise exposure and children's weight status, with two reporting a positive association and the other two reporting no association.^{29,34,38,66} One study showed that parental perception of exposure to traffic noise had no clear association with childhood obesity.⁶⁰

3.8 | Study quality assessment

The criterion-specific and global ratings of study quality were assessed (Table S4). Of the 39 studies included, 14 had a score of 10 or higher and 25 had a score of 9 or lower. All studies scored 9.07 on average, with a range from 5 to 12. Some studies failed to meet the item 12, as observational studies were difficult to achieve blindness. Also, measurements of exposure(s) cannot be obtained prior to the outcome(s) for cross-sectional studies. Most studies did not explicitly provide justification for a sample size, power description, or variance and effect estimates (item 5).

4 | DISCUSSION

There has been a growing body of research on the association between traffic-related factors and childhood obesity, but no systematic review has been conducted. After reviewing 39 studies conducted in 18 countries, we summarized the key characteristics of the studies that reported statistically significant correlation. For study design, there were some differences in age at baseline and measures of exposure and outcomes. We found that traffic-related factors can affect weight-related behaviours while long-term traffic-related air pollution was weakly positively associated with children's BMI growth. Associations between traffic density and noise and weight status were generally not significant. Lack of consistent measurement of individual exposure to traffic-related factors could be a possible reason for the mixed findings.

For the mechanisms linking traffic-related factors to obesity, this review confirms the previously identified theoretical framework that integrates behaviour and exposure-based pathways in understanding the impact of traffic-related factors on health.⁶⁷ Traffic flow is usually related to perceived safety and land use, which may further affect outdoor PA.⁵⁴ Traffic-related air pollution may affect children's weight status through increased caloric intake caused by pro-inflammatory central nervous system's effects of airborne particles on appetite control, reduced PA, or changes in basal metabolism due to effects on mitochondria and brown adipose tissue.^{25,68} It may also lead to metabolic dysfunction by increased oxidative stress and adipose tissue inflammation and weaken the utilization of glucose in skeletal muscle.⁶⁹ Traffic noise may influence body composition through stress, sleep disturbances, and caloric intake.³⁴ Based on these theoretical rationales and significant findings in previous studies, this review found that traffic-related factors can affect parents' or children's PA, eating habit, and psychology through traffic flow, noise, pollution, and sense of safety.

However, most of the studies we reviewed here indicate that the strength of the relationships between traffic-related factors and weight-related outcomes among children appears to be marginal with small effect sizes, calling for more robust evidence to establish causality. Moreover, due to the small number of studies in meta-analysis and considerable heterogeneity, evidence on the association between traffic-related factors and obesity is still insufficient. More detailed investigations are needed to establish a causal link between traffic and childhood obesity and to identify novel targets for intervention. Longitudinal studies seem to provide more significant results than cross-sectional studies, of which significantly related results accounted for 75% (12/16) in longitudinal studies while the percentage is 29% (2/7) in cross-sectional studies.

Some studies showed that exposure to traffic-related factors in early life (e.g., in utero and first year of life), reported as periods of rapid growth that are highly susceptible to environmental influences,⁷⁰ was more critical than mid-childhood exposure and may significantly alter childhood growth trajectories.^{27,71} The research team explored the possibilities of differential risk factors among age groups. However, the review did not show any trend according to age groups, while significant results accounted for 67% (10/15), 73% (8/11), and 25% (1/4) of the total reports for weight-related outcomes, among children less than or equal to 6, 6 to 12, and 13 to 18 years old, respectively. Other environmental factors, such as social and neighbourhood contextual factors, may also affect obesity in children. Therefore, all studies included in the review adjusted for some environmental factors other than traffic-related factors. We summarized these other environmental factors into three groups: individual-, family-, and community-level factors. As for their respective influence, Hinojosa et al⁵¹ reported that several variables representing within- and school-neighbourhood factors were the most important contributors to childhood obesity, in addition to individual-level factors, including race and gender.

Some studies in our review (6/23) used BMI as an outcome. However, some other studies argued that while BMI seems to be an appropriate proxy for measuring adiposity in adults, it may not be as useful in children. This is because children often experience rapid and fluctuating growth depending on their pubertal status and show different physical maturation patterns by gender and ethnicity.^{14,72} In our review, two studies included other anthropometric measures, such as waist circumference, waist-to-hip ratio, total and high-density lipoprotein (HDL) cholesterol, triceps, and subscapular skinfolds as indicators of childhood obesity. While most of these studies showed no significant association between traffic exposure and overweight/obesity outcome, a significant association was found for waist circumference (cm) and skinfolds.^{47,56} This suggests that further studies of childhood obesity would benefit from using other anthropometric measures than BMI, such as waist circumference (a risk factor for type II diabetes and coronary heart disease), waist-to-hip ratio, and direct measurements of body fat.

There are a few limitations in this review. First, measures of the traffic-related factors, weight-related outcomes/behaviours varied across studies, which led to a smaller number of studies to conduct the

meta-analyses. Therefore, no covariates were adjusted for the subgroup analyses, which resulted in reduced comparability among different subgroups. Inconsistency in our analyses was still largely unexplained. It is likely driven by true heterogeneity in participants' characteristics, covariates, traffic measurements, outcomes, and study design. Second, there are common problems when assessing the relationship between environmental factors and health outcomes. Few studies made an accurate distinction between individual exposures and environmental exposures, which may have led to weakening the effect.⁷³ Third, wearable or mobile sensors need to be used in future studies to measure personalized exposure to environmental stressors.^{74,75} Finally, there could be other unexplored pathways that might have confounded the results, such as psychology, sleep, endocrine, and exercises. Many other factors, such as household environments and social network factors, may have also influenced the results.

To advance the field, long-term changes in traffic patterns, pollution, and noise in relation to weight outcomes should be investigated. More longitudinal studies with uniform measurements of multiple traffic exposures and weight related outcomes would be needed to ensure that more reliable comparisons can be made.⁷⁶ Also, further studies may explore other pathways to understand to what extent other social and built environmental factors could mediate the relationships between traffic exposures and behavioural and biological factors associated with obesity during childhood.

5 | CONCLUSIONS

The relationship between traffic environmental factors and obesity is increasingly getting more attention in the field of children's health and lifecourse epidemiology. This review and meta-analysis fills an important research gap on this topic by systematically pooling existing studies on the relationship between traffic density, traffic pollution, traffic noise, traffic safety, and weight-related outcomes/behaviours (e.g., adiposity measures, PA, diet, and other dependent variables) in children. We found that traffic-related factors can affect weight-related behaviours, and long-term traffic pollutions were weakly positively associated with children's BMI growth. However, associations between traffic density, traffic noise, and weight status were rather inconclusive. Interestingly, longitudinal studies provided more significant results for weight-related outcomes compared to cross-sectional studies.

Through this review, we intend to bring more attention to emerging health challenges related to growing traffic problems in low-income countries; offer timely insights on the relationship between traffic-related factors and childhood obesity; and call for a more uniform approach to measuring traffic-related factors and weight-related outcomes/behaviours. We also highlight the need for a more in-depth investigation on the mechanisms linking traffic-related factors to childhood obesity, possibly through behavioural, psychological, and social contextual factors. More thorough understanding of these

mechanisms will help make a tangible shift in policy to move from an obesogenic to a salutogenic environment, ultimately leading to downstream impacts on individual behavioural change and obesity outcomes.

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CONFLICTS OF INTEREST

We declare no conflicts of interest.

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REFERENCES

- Han JC, Lawlor DA, Kimm SY. Childhood obesity. *Lancet*. 2010;375(9727):1737-1748.
- Ng M, Fleming T, Robinson M, et al. Global, regional, and national prevalence of overweight and obesity in children and adults during 1980-2013: a systematic analysis for the Global Burden of Disease Study 2013. *Lancet*. 2014;384(9945):766-781.
- Jia P, Xue H, Zhang J, Wang Y. Time trend and demographic and geographic disparities in childhood obesity prevalence in China—evidence from twenty years of longitudinal data. *Int J Environ Res Public Health*. 2017;14(4). <https://doi.org/10.3390/ijerph14040369>
- Hales CM, Carroll MD, Fryar CD, Ogden CL. Prevalence of obesity among adults and youth: United States, 2015-2016. *NCHS Data Brief*. 2017;288:1-8.
- Ogden CL, Carroll MD, Fryar CD, Flegal KM. Prevalence of obesity among adults and youth: United States, 2011-2014. *NCHS Data Brief*. 2015;219:1-8.
- World Health Organization. Facts and figures on childhood obesity. 2017 [WWW document] URL: <https://www.who.int/end-childhood-obesity/facts/en/>.
- World Health Organization. WHO-led commission on ending childhood obesity meets to develop global responses to obesity epidemic. 2015 [WWW document] URL: <https://www.who.int/end-childhood-obesity/news/echo-second-meeting/en/>.
- Zhang X, Zhang M, Zhao Z, et al. Geographic variation in prevalence of adult obesity in China: results from the 2013-2014 National Chronic Disease and Risk Factor Surveillance. *Ann Intern Med*. 2019. <https://doi.org/10.7326/M19-0477>
- Gungor NK. Overweight and obesity in children and adolescents. *J Clin Res Pediatr Endocrinol*. 2014;6(3):129-143.
- Nogrady B. Childhood obesity: a growing concern. *Nature*. 2017;551(7681). <https://www.ncbi.nlm.nih.gov/pubmed/29168809>
- Wang Y, Jia P, Cheng X, Xue H. Improvement in food environments may help prevent childhood obesity: evidence from a 9-year cohort study. *Pediatr Obes*. 2019;14(10):e12536. <https://www.ncbi.nlm.nih.gov/pubmed/31148419>

12. Zhou Q, Zhao L, Zhang L, et al. Neighborhood supermarket access and childhood obesity: a systematic review. *Obes Rev*. 2021;22(Suppl 1):e12937.
13. Jia P, Luo M, Li Y, Zheng JS, Xiao Q, Luo J. Fast-food restaurant, unhealthy eating, and childhood obesity: a systematic review and meta-analysis. *Obes Rev*. 2021;22(Suppl 1):e12944.
14. Sahoo K, Sahoo B, Choudhury AK, Sofi NY, Kumar R, Bhadoria AS. Childhood obesity: causes and consequences. *J Family Med Prim Care*. 2015;4(2):187-192.
15. Xin J, Zhao L, Wu T, et al. Association between access to convenience stores and childhood obesity: a systematic review. *Obes Rev*. 2021;22(Suppl 1):e12908.
16. Jia P, Xue H, Cheng X, Wang Y. Effects of school neighborhood food environments on childhood obesity at multiple scales: a longitudinal kindergarten cohort study in the USA. *BMC Med*. 2019;17(1):99-99.
17. Jia P, Xue H, Cheng X, Wang Y, Wang Y. Association of neighborhood built environments with childhood obesity: evidence from a 9-year longitudinal, nationally representative survey in the US. *Environ Int*. 2019;128:158-164.
18. Kamath CC, Vickers KS, Ehrlich A, et al. Clinical review: behavioral interventions to prevent childhood obesity: a systematic review and metaanalyses of randomized trials. *J Clin Endocrinol Metab*. 2008;93(12):4606-4615.
19. Jia P, Cheng X, Xue H, Wang Y. Applications of geographic information systems (GIS) data and methods in obesity-related research. *Obes Rev*. 2017;18(4):400-411.
20. Seidell JC, Halberstadt J. The global burden of obesity and the challenges of prevention. *Ann Nutr Metab*. 2015;66(Suppl 2):7-12.
21. Yang Z, Jia P, Liu W, Yin H. Car ownership and urban development in Chinese cities: a panel data analysis. *J Transp Geogr*. 2017;58(1):127-134.
22. Diez FP, Cacheda MC, Sinca JC. Stage of historical evolution of private vehicle ownership in the city of Barcelona. *Tran Resear Procedia*. 2016;18:140-147.
23. Statista. Percentage of households owning a car in selected countries in 2014, by country. 2019 [WWW document] URL: <https://www.statista.com/statistics/516280/share-of-households-that-own-a-passenger-vehicle-by-country/>.
24. World Health Organization. Global status report on road safety 2018. 2018 [WWW document] URL: https://www.who.int/violence_injury_prevention/road_safety_status/2018/en/.
25. Jerrett M, McConnell R, Wolch J, et al. Traffic-related air pollution and obesity formation in children: a longitudinal, multilevel analysis. *Environ Health*. 2014;13(1):49. <https://www.ncbi.nlm.nih.gov/pubmed/?term=Trafficrelated+air+pollution+and+obesity+formation+in+children>
26. Stansfeld S, Clark C. Health effects of noise exposure in children. *Current Envi Health Reports*. 2015;2(2):171-178.
27. Kim JS, Alderete TL, Chen Z, et al. Longitudinal associations of in utero and early life near-roadway air pollution with trajectories of childhood body mass index. *Environ Health*. 2018;17(1):64.
28. Jerrett M, McConnell R, Chang CCR, et al. Automobile traffic around the home and attained body mass index: a longitudinal cohort study of children aged 10-18 years. *Prev Med*. 2010;50:S50-S58.
29. Weyde KV, Krog NH, Oftedal B, et al. A longitudinal study of road traffic noise and body mass index trajectories from birth to 8 years. *Epidemiology*. 2018;29(5):729-738.
30. Tang-Peronard JL, Andersen HR, Jensen TK, Heitmann BL. Endocrine-disrupting chemicals and obesity development in humans: a review. *Obes Rev*. 2011;12(8):622-636.
31. Borenstein M, Hedges LV, Higgins JPT, Rothstein HR. *Introduction to meta-analysis*. John Wiley & Sons; 2011.
32. Alderete TL, Habre R, Toledo-Corral CM, et al. Longitudinal associations between ambient air pollution with insulin sensitivity, beta-cell function, and adiposity in Los Angeles Latino children. *Diabetes*. 2017;66(7):1789-1796.
33. Alton D, Adab P, Roberts L, Barrett T. Relationship between walking levels and perceptions of the local neighbourhood environment. *Arch Dis Child*. 2007;92(1):29-33.
34. Bloemsma LD, Wijga AH, Klompaker JO, et al. The associations of air pollution, traffic noise and green space with overweight throughout childhood: the PIAMA birth cohort study. *Environ Res*. 2018;169:348-356.
35. Bringolf-Isler B, Grize L, Mäder U, Ruch N, Sennhauser FH, Braun-Fahrlander C. Built environment, parents' perception, and children's vigorous outdoor play. *Prev Med*. 2010;50(5-6):251-256.
36. Bungum TJ, Lounsbury M, Moonie S, Gast J. Prevalence and correlates of walking and biking to school among adolescents. *J Community Health*. 2009;34(2):129-134.
37. Chen Z, Herting MM, Chatzi L, et al. Regional and traffic-related air pollutants are associated with higher consumption of fast food and trans fat among adolescents. *Am J Clin Nutr*. 2019;109(1):99-108. <https://www.ncbi.nlm.nih.gov/pubmed/30596809>
38. Christensen JS, Hjortebjerg D, Raaschou-Nielsen O, Ketzler M, Sorensen TIA, Sorensen M. Pregnancy and childhood exposure to residential traffic noise and overweight at 7 years of age. *Environ Int*. 2016;94:170-176.
39. Cradock AL, Melly SJ, Allen JG, Morris JS, Gortmaker SL. Youth destinations associated with objective measures of physical activity in adolescents. *Journal of Adol Heal*. 2009;45(3):S91-S98.
40. Crawford D, Cleland V, Timperio A, et al. The longitudinal influence of home and neighbourhood environments on children's body mass index and physical activity over 5 years: the CLAN study. *Int J Obes (Lond)*. 2010;34(7):1177-1187.
41. de Vries SI, Bakker I, van Mechelen W, Hopman-Rock M. Determinants of activity-friendly neighborhoods for children: results from the SPACE study. *Am J Health Promot*. 2007;21(4 Suppl):312-316.
42. Dong GH, Qian ZM, Liu MM, et al. Ambient air pollution and the prevalence of obesity in chinese children: the seven northeastern cities study. *Obesity*. 2014;22(3):795-800.
43. Duncan DT, Sharifi M, Melly SJ, et al. Characteristics of walkable built environments and BMI z-scores in children: evidence from a large electronic health record database. *Environ Health Perspect*. 2014;122(12):1359-1365.
44. Dunton GF, Intille SS, Wolch J, Pentz MA. Investigating the impact of a smart growth community on the contexts of children's physical activity using Ecological Momentary Assessment. *Health Place*. 2012;18(1):76-84.
45. Esteban-Cornejo I, Carlson JA, Conway TL, et al. Parental and adolescent perceptions of neighborhood safety related to adolescents' physical activity in their neighborhood. *Res Q Exerc Sport*. 2016;87(2):191-199.
46. Evans GW, Lercher P, Meis M, Ising H, Kofler WW. Community noise exposure and stress in children. *J Acou Societ Am*. 2001;109(3):1023-1027.
47. Fioravanti S, Cesaroni G, Badaloni C, Michelozzi P, Forastiere F, Porta D. Traffic-related air pollution and childhood obesity in an Italian birth cohort. *Environ Res*. 2018;160:479-486.
48. Gose M, Plachta-Danielzik S, Willie B, Johannsen M, Landsberg B, Muller MJ. Longitudinal influences of neighbourhood built and social environment on children's weight status. *Int J Environ Res Public Health*. 2013;10(10):5083-5096.
49. Grassi T, de Donno A, Bagordo F, et al. Socio-economic and environmental factors associated with overweight and obesity in children aged 6-8 years living in five Italian cities (the MAPEC_LIFE Cohort). *Int J Environ Res Public Health*. 2016;13(10):1002. <https://www.ncbi.nlm.nih.gov/pubmed/2772193>
50. Gustat J, Richards K, Rice J, Andersen L, Parker-Karst K, Cole S. Youth walking and biking rates vary by environments around 5 Louisiana schools. *J Sch Health*. 2015;85(1):36-42.

51. Hinojosa AMO, MacLeod KE, Balmes J, Jerrett M. Influence of school environments on childhood obesity in California. *Environ Res*. 2018; 166:100-107.
52. Huang JV, Leung GM, Schooling CM. The association of air pollution with body mass index: evidence from Hong Kong's "Children of 1997" birth cohort. *Int J Obes (Lond)*. 2019;43(1):62-72. <https://www.ncbi.nlm.nih.gov/pubmed/29686381>
53. Jarrett RL, Bahar OS, McPherson E, Williams DA. No child left inside the built environment and caregiver strategies to promote child physical activity. *J Leisure Res*. 2013;45(4):485-513.
54. Lange D, Wahrendorf M, Siegrist J, Plachta-Danielzik S, Landsberg B, Muller MJ. Associations between neighbourhood characteristics, body mass index and health-related behaviours of adolescents in the Kiel Obesity Prevention Study: a multilevel analysis. *Eur J Clin Nutr*. 2011;65(6):711-719.
55. Larsen K, Gilliland J, Hess PM. Route-based analysis to capture the environmental influences on a child's mode of travel between home and school. *Ann Assoc American Geographers*. 2012;102(6):1348-1365.
56. Lovasi GS, Jacobson JS, Quinn JW, Neckerman KM, Ashby-Thompson MN, Rundle A. Is the environment near home and school associated with physical activity and adiposity of urban preschool children? *J Urban Health-Bulle New York Academ Medicine*. 2011;88(6):1143-1157.
57. McConnell R, Shen E, Gilliland FD, et al. A longitudinal cohort study of body mass index and childhood exposure to secondhand tobacco smoke and air pollution: the Southern California Children's Health Study. *Environ Health Perspect*. 2015;123(4):360-366.
58. McTigue KM, Cohen ED, Moore CG, Hipwell AE, Loeber R, Kuller LH. Urban neighborhood features and longitudinal weight development in girls. *Am J Prev Med*. 2015;49(6):902-911.
59. Sakai R. Relationship between prevalence of childhood obesity in 17-year-olds and socioeconomic and environmental factors: prefecture-level analysis in Japan. *Asia Pac J Public Health*. 2013;25(2):159-169.
60. Schule SA, Fromme H, Bolte G. Built and socioeconomic neighbourhood environments and overweight in preschool aged children. A multilevel study to disentangle individual and contextual relationships. *Environ Res*. 2016;150:328-336.
61. Su JG, Jerrett M, McConnell R, et al. Factors influencing whether children walk to school. *Health Place*. 2013;22:153-161.
62. Timperio A, Salmon J, Telford A, Crawford D. Perceptions of local neighbourhood environments and their relationship to childhood overweight and obesity. *Int J Obes (Lond)*. 2005;29(2):170-175.
63. Timperio A, Jeffery RW, Crawford D, Roberts R, Giles-Corti B, Ball K. Neighbourhood physical activity environments and adiposity in children and mothers: a three-year longitudinal study. *Int J Behav Nutr Phys Act*. 2010;7:18. <https://www.ncbi.nlm.nih.gov/pubmed/20170507>
64. Tung SEH, Ng XH, Chin YS, Taib MNM. Associations between parents' perception of neighbourhood environments and safety with physical activity of primary school children in Klang, Selangor, Malaysia. *Child Care Health Dev*. 2016;42(4):478-485.
65. Vanhelst J, Béghin L, Salleron J, et al. A favorable built environment is associated with better physical fitness in European adolescents. *Prev Med*. 2013;57(6):844-849.
66. Wallas A, Ekström S, Bergström A, et al. Traffic noise exposure in relation to adverse birth outcomes and body mass between birth and adolescence. *Environ Res*. 2018;169:362-367.
67. Frank LD, Iroz-Elardo N, MacLeod KE, Hong A. Pathways from built environment to health: a conceptual framework linking behavior and exposure-based impacts. *J Transp Health*. 2019;12:319-335.
68. McConnell R, Gilliland FD, Goran M, Allayee H, Hricko A, Mittelman S. Does near-roadway air pollution contribute to childhood obesity? *Pediatr Obes*. 2016;11(1):1-3.
69. An R, Ji M, Yan H, Guan C. Impact of ambient air pollution on obesity: a systematic review. *Int J Obes (Lond)*. 2018;42(6):1112-1126.
70. Adair LS. Child and adolescent obesity: epidemiology and developmental perspectives. *Physiol Behav*. 2008;94(1):8-16.
71. Zheng T, Zhang J, Sommer K, et al. Effects of environmental exposures on fetal and childhood growth trajectories. *Ann Glob Health*. 2016;82(1):41-99.
72. Lazarus R, Baur L, Webb K, Blyth F. Body mass index in screening for adiposity in children and adolescents: systematic evaluation using receiver operating characteristic curves. *Am J Clin Nutr*. 1996;63(4):500-506.
73. Jia P. Spatial lifecourse epidemiology. *The Lancet Planetary health*. 2019;3(2):e57-e59.
74. Jia P, Lakerveld J, Wu J, et al. Top 10 research priorities in spatial lifecourse epidemiology. *Environ Health Perspect*. 2019;127(7):74501. <https://www.ncbi.nlm.nih.gov/pubmed/?term=Top+10+Research+Priorities+in+Spatial+Lifecoursehttps://www.ncbi.nlm.nih.gov/pubmed/20170507>
75. Jia P, Xue H, Yin L, Stein A, Wang M, Wang Y. Spatial technologies in obesity research: current applications and future promise. *Trends Endocrinol Metab*. 2019;30(3):211-223.
76. Jia P, Yu C, Remais J, et al. Spatial lifecourse epidemiology reporting standards (ISLE-ReSt) statement. *Health Place*. 2019. <https://www.sciencedirect.com/science/article/pii/S1353829219306355>

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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