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Street connectivity, physical activity, and childhood obesity: A systematic review and meta-analysis

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[Correction added on 8 February 2021, after first online publication: Peng Jia's correspondence details have been updated.]

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Summary

Street connectivity, as a neighbourhood built environmental factor, may affect individual physical activity (PA) and subsequently weight status. However, these associations remain inconclusive. This study aimed to systematically review the association between street connectivity and childhood obesity. A literature search was conducted in the Cochrane Library, PubMed, and Web of Science for articles published before January 1, 2019. All original studies that investigated the association between street connectivity and weight-related behaviours or outcomes among children and adolescents were included. Forty-seven articles were identified, including eight longitudinal and 41 cross-sectional studies conducted in eight countries. The sample size ranged from 88 to 46 813. Street intersection density (SID), measured by Geographic Information Systems in 36 studies and reported in 13 studies, was the main indicator used to represent street connectivity. Forty-four studies examined the association between SID and weight-related behaviours, including overall PA (n = 15), moderate-to-vigorous PA (n = 13), active transport (n = 12), dog walking (n = 1), walking (n = 1), sedentary behaviours (n = 2), and TV viewing (n = 1). Fifteen studies focused on the association between SID and weight-related outcomes. Overall, evidence from this systematic review and meta-analyses suggested a positive association between street connectivity and PA. However, it was difficult to draw a conclusion on the association between street connectivity and BMI. More longitudinal evidence is needed to confirm the causal association between street connectivity and weight status.

KEYWORDS

built environment, obesity, physical activity, street connectivity

1 | INTRODUCTION

Excess body weight, often classified as overweight or obesity, is a leading cause of morbidity and premature mortality worldwide. From 1980 to 2013, the global prevalence of overweight and obesity has risen by 27.5% for adults and 47.1% for children. In developed countries, childhood overweight and obesity have increased significantly during 1980-2013 from 16.9% to 23.8% for boys and from 16.2% to 22.6% for girls. The prevalence of overweight and obesity in developing countries has also been elevated among children and adolescents, increasing from 8.1% to 12.9% for boys and 8.4% to 13.4% for girls during 1980-2013.[1] Serious health consequences are associated with overweight and obesity, such as cardiovascular diseases, hypertension, metabolic syndromes, type 2 diabetes, and cancers.[2] Also, childhood overweight and obesity tend to persist into adulthood. Therefore, control and prevention of childhood obesity should be prioritized.

It is widely accepted that the neighbourhood built environment may affect individual weight status via interacting with personal characteristics and influencing human behaviours. Street connectivity is one such environmental factor, which is defined as the directness of links and density of connections in street networks. It is usually denoted by the density of intersections of three or more street segments per square kilometre, also referred to as street intersection density (SID). Several studies have demonstrated links between street connectivity and children's outdoor physical activity (PA),[3] such as walking, playing, and cycling.[4,5] While some studies also revealed a negative association between street connectivity and childhood obesity risk, findings remain inconclusive in terms of effect direction and size.[6,7] To the knowledge of the authors, there has not been any review on these associations.

This study aimed to systematically review the association between street connectivity and weight-related behaviours/outcomes. In this review, we examined a full range of measures of street connectivity at multiple sites (eg, residential, school, and workplace neighbourhoods) for a comprehensive understanding of their associations with children's outdoor behaviours and childhood obesity. Our results are expected to be used for designing effective interventions and policies for the prevention of childhood obesity.

2 | METHODS

A systematic review and meta-analysis was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses.

2.1 | Study selection criteria

We included studies that met all of the following criteria: (a) study subject (children and adolescents aged less than 18); (b) study design (cross-sectional studies and longitudinal studies including prospective and retrospective cohort studies); (c) study outcome (weight-related behaviours [eg, PA, sedentary behaviours, and dietary behaviours] and/or outcomes [eg, body mass index (BMI, kg/m^2), overweight and obesity, waist circumference, waist-to-hip ratio, and body fat]); (d) article type (peer-reviewed original research); (e) time of publication (from the inception of an electronic bibliographic database to 31 December 2018); and (f) language (English).

We excluded any of the following studies: (a) studies that incorporated no measures of street connectivity or weight-related behaviours/outcomes; (b) studies without the inclusion of human participants; (c) controlled experiments conducted in manipulated rather than naturalistic settings; (d) studies not presented in English; or (e) letters, editorials, study/review protocols, or review studies.

2.2 | Search strategy and data extraction

A keyword search was performed in three electronic bibliographic databases: PubMed, Web of Science, and Cochrane Library. The search strategy included all possible combinations of three groups of keywords related to street connectivity, children, and weight-related behaviours or outcomes. Details of search strategies could be found in Appendix A.

Titles and abstracts of all records identified through the keyword search were screened against the study selection criteria by P.J. and Y.Z. Discrepancies were compiled by Y.Z. and additionally screened by Z.W. P.J., Y.Z., and Z.W. jointly discussed and determined the list of articles for the full-text review. P.J. and Y.Z. independently reviewed the full texts of all articles in the list and jointly discussed and determined the final list of the included articles. Then P.J. and Y. Z. used the same standardized data extraction form to independently extract data from each included study. Z.W. resolved discrepancies, and Y.Z. reorganized and finalized all information tables.

2.3 | Data preparation for meta-analysis

Twenty-two studies were included in the meta-analysis. Studies were excluded as results of missing effect size information,[8,9] lacking information for effect size transformation,[10-20] being the only study using a specific pair of measures of street accessibility and weight-related behaviours/outcomes,[21-23] being the only study of that type,[7,24,25] or focus on a unique population.[26]

As most of the included studies reported effect sizes in the form of odds ratio (OR),[4,27-36] we retained OR when available and transformed all other effect size measures into OR when needed for meta-analyses. Wherever effect sizes were not available, we collected[27,37,38] or transformed unstandardized regression coefficients[39,40] (based on the reported standard deviations) into standardized coefficients, which were then coded into correlation coefficients[41] for OR transformation. One article reported the relative risk (RR),[3] which was transformed into OR using the equation OR=[RR*(1-P)]/(1-RR*P), where P denotes the prevalence in control or reference group. The Cohen *d*[42] and correlation coefficients[43-45] were directly transformed into ORs. For articles reporting effect sizes for multiple outcomes, we focused on results for PA. Wherever multiple results were presented for different levels of measures of street connectivity, the measure calculated within the largest area (eg, administrative unit or buffer zone) was chosen for meta-analyses.

2.4 | Study quality assessment

We used the National Institutes of Health's Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies to assess the quality of each included study. This assessment tool rates each study on a basis of 14 criteria (Appendix B). For each criterion, a score of one was assigned if "yes" was the response, and a score of zero was assigned otherwise (ie, an answer of "no," "not applicable," "not reported," or "cannot determine"). A study-specific global score ranging from 0 to 14 was calculated by summing up scores across all criteria. The study quality assessment helped measure the strength of scientific evidence, but was not used to determine the inclusion of studies.

2.5 | Statistical analysis

All statistical analyses were conducted in the Comprehensive Meta Analysis Version 3.3.070.[46] A random effect model was used to combine ORs and 95% confidence intervals (CIs), as we were estimating a distribution of effect sizes. The risk of publication bias was assessed using funnel plots, where the logged ORs were plotted against their corresponding standard errors for each study. Two formal tests were also used for testing publication bias, including Egger regression intercept test and Begg rank correlation test. Heterogeneity between studies was assessed by the chi-squared heterogeneity test (I^2), where I^2 value of 25%, 50%, and 75% indicated low, medium, and high heterogeneity, respectively.

3 | RESULTS

3.1 | Study selection

Figure 1 showed the flowchart of study inclusion. Overall, 217 non-duplicated articles were included in the title and abstract screening. Articles were excluded due to irrelevant themes (n = 102), adult population (n = 46), review papers (n = 3), not written in English (n = 1), study design (n = 2), or lack of measures of street connectivity or weight-related behaviours/outcomes (n = 16). The remaining 47 articles were included in the full-text review.

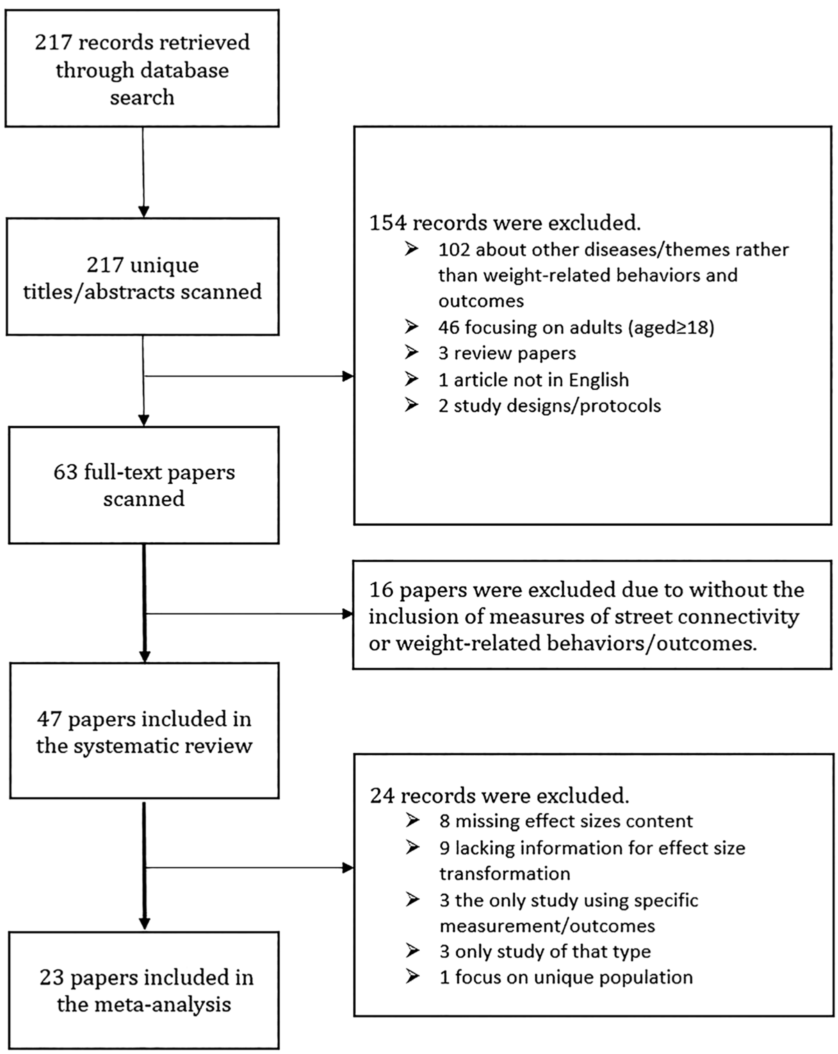

FIGURE 1 Study exclusion and inclusion flowchart

TABLE 1 Basic characteristics of 47 studies included in this study (see [ref] in the main text) [Colour table can be viewed at wileyonlinelibrary.com]

Author (year) [ref][a]	Study design[b]	Study area [scale][c]	Sample size	Sample age (yrs, range and/or mean ± SD)[d]	Sample characteristics (follow-up status for longitudinal studies)	Statistical model
Boone-Heinonen (2010)[11]	L	US [N]	12 701	11-12 in 1994-1995	School children (followed up from 1994-1995 to 2001-2002, with two repeated measures and an attrition rate of 41.6%)	Fixed effects Poisson regression
Boone-Heinonen (2010)[12]	C	US [N]	17 659	11-12 in 1994-1995	School children	Negative binomial regression
Boone-Heinonen (2010)[15]	C	US [N]	12 701	Wave I: 11-12 in 1994-1995; Wave III: 18-19 in 2001-2002	Representative of the US adolescents	Negative binomial generalized estimating equations
Buck (2015)[38]	C	Delmenhorst, Germany [C]	400	2-9 in 2007-2008	Children collected during the baseline survey of the IDEFICS study	Gamma log-regression
Bungum (2009)[4]	C	Northern Utah community, US [S]	2692		High school student	Bivariate correlations and logistic regression
Cain (2017)[21]	C	Seattle, San Diego, Baltimore and Washington, US [C4]	1655		NA	Mixed linear regression
Carlson (2014)[64]	C	Baltimore and Seattle, US [C2]	294	12-15 in 2011	School children	Mixed effects multinomial regression models
Carlson (2015)[40]	C	Baltimore and Seattle, US [C2]	690	12-16 in 2009-2011	School children	Negative binomial model
Carver (2010)[13]	L	Melbourne, Australia [C]	446	170 (8-9) and 276 (13-15) in 2004	NA (followed up from 2004 to 2006, with two repeated measures and an attrition rate of 26.5%)	Multiple linear regression
Cohen (2006)[17]	C	US [N]	1554	sixth-grade in 2003	Adolescent girls	Multilevel linear regression
Crawford (2010)[24]	L	Melbourne, Australia [C]	301	10-12 in 2001	School children (followed up from 2001 to 2006, with three repeated measures and an attrition rate of 56.7%)	Generalized estimating equations
D'Haese (2015)[62]	C	Ghent, Belgian [C]	606	9-12 in 2011-2013	Elementary school children	Multilevel logistic regression
Dalton (2011)[30]	C	New Hampshire and Vermont, US [S2]	1552	Grades 4-6 in 2007-2008	Adolescent in two predominantly rural states	Multilevel linear regression
Datar (2015)[26]	C	US [N]	903	12-13 in 2013	From the Military Teenagers Environments, Exercise, and Nutrition Study	Multivariate regression
Deforche (2010)[42]	C	Belgian [N]	1445	17.4 in 2008	School children	Moderated multilevel regression
Duncan (2014)[47]	C, L	Massachusett, US [S]	46813	4-19 in 2011-2012	Adolescents from 14 pediatric practices of Harvard Vanguard Medical Associates	Multivariable cross-sectional

(Continues)

TABLE 1 (Continued)

Author (year) [ref][a]	Study design[b]	Study area [scale][c]	Sample size	Sample age (yrs, range and/or mean ± SD)[d]	Sample characteristics (follow-up status for longitudinal studies)	Statistical model
Engelberg (2015)[27]	C	Seattle and Baltimore, US [C2]	925	12-17 in 2009-2011	NA	Ecological models
Frank (2007)[31]	C	Atlanta, US [C]	3161	5-20 in 2001-2002	NA	Logistic regression
Ghekiere (2015)[16]	C	Melbourne, Australia [C]	677	10-12 in	Elementary school children	Multilevel linear regression
Grafova (2010)23	C	US [N]	2482	5-18 in 2002-2003	NA	Logistic regression
Hinckson (2017)[28]	C	Auckland and Wellington, New Zealand [C2]	524	15.78 ± 1.62 in 2013-2014	School children	Additive mixed models
Kamruzzaman (2013)[18]	C	Northern Ireland [S]	1624	Primary school to secondary school	School children	Multivariate multiple regression
Larsen (2012)[33]	C	London, Canada [C]	614	Grade 7-8 in 2006-2007	School children	Univariate logistic regression
Larsen (2015)[45]	C	Toronto and Hamilton, Canada [C2]	559	2011	Elementary school children	Binomial logistic regression
Loon (2014)[14]	C	Vancouver, Canada [C]	366	8-11 in 2005-2006	Children in the AS!BC trial	Generalized estimating equation
Mecredy (2011)[3]	C	Canada [N]	8535	Grades 6-10 in 2006	School children	Bivariate multilevel regression
Meng (2018)[19]	C	Shenzhen, China [C]	1257	12-15	School children	Binary logistic regression
Millstein (2011)[8]	C	San Diego, Boston and Cincinnati, US [C3]	241	104 (5-11) and 137 (12-18) in 2005-2006	NA	Multilevel linear regression
Mitra (2012)[9]	C	Toronto, Canada [C]	2520	11-12 in 2006	School children	Binomial logistic regression
Molina-García (2015)[37]	L	Valencia, Spain [C]	244	17.6 in 2011	School children (followed up from 2011 to 2012, with two repeated measures and an attrition rate of 54%)	Stepwise regression
Moran (2016)[65]	C	Rishon LeZion, Israel [C]	573	10-12 in 2010-2011	School children	Multivariate logistic regression
Mota (2007)[32]	C	Aveiro District, Portugal [C]	705	14.7 in 2004	Adolescent girls	Logistic regression
Mota (2011)[61]	C	Aveiro Region, Portugal [C]	599	14.7 (SD=1.6) in 2006	Adolescent girls	Logistic regression
Nelson (2010)[34]	C	Ireland [N]	2159	16.04 ± 0.66	School children	Logistic regression
Norman (2006)[44]	C	San Diego country, US [CT]	799	11-15	Adolescents recruited through their primary care providers	Multilevel linear regression
Oliver (2015)[10]	C	Auckland, New Zealand [C]	236	9-13 in 2011-2012	School children	Generalized estimating equation modelling
Oreskovic (2014)[63]	C	Houston, US [C]	149	9.7 in 2009	Low-income children who had participated in the walking school bus RCT and lived within one mile of school	Multi-level mixed models

(Continues)

TABLE 1 (Continued)

Author (year) [ref][a]	Study design[b]	Study area [scale][c]	Sample size	Sample age (yrs, range and/or mean ± SD)[d]	Sample characteristics (follow-up status for longitudinal studies)	Statistical model
Roemmich (2007)[43]	C	Erie County, New York, US [CT]	88	8-12	NA	Multilevel regression
Rosenberg (2009)[60]	C	San Diego, Boston and Cincinnati, US [C3]	287	116 (5-11) and 171 (12-18) in 2005	NA	Single measure intraclass correlation coefficients
Rothman (2014)[41]	C	Toronto, Canada [C]	118 schools	Junior kindergarten to grades 6 in 2010-2011	Children live within walking distance to the school	Negative binomial model
Schipperijn (2015)[39]	L	Denmark [N]	177	15 in 2003-2004	Followed up from 2003-2004 to 2009-2010, with two repeated measures and an attrition rate of 77.0%	Multivariable analysis of variance
Spence (2008)[25]	C	Edmonton, Canada [C]	501	4-6 in 2004	Attended one of 10 health centers for preschool immunization within the Capital Health region	Separate logistic regressions
Tappe (2013)[29]	C	San Diego and Seattle, US [C2]	724	6-11 in 2007-2009	NA	Linear and logistic bivariate model
Timperio (2010)[7]	L	Melbourne, Australia [C]	409	140 (5-6) and 269 (10-12) in 2001	Elementary school children (followed up from 2001 to 2004, with two repeated measures and an attrition rate of 30.7%)	Multivariable linear regression
Timperio (2012)[22]	C, L	Melbourne and Geelong, Australia [C2]	262	11.2	School children (followed up from 2006 to 2008, with two repeated measures and an attrition rate of 27%)	Linear regression
Trapp (2011)[36]	C	Perth, Australia [N]	1197	Grade 5-7 in 2007	Elementary school children	Multivariate logistic regression
Trapp (2012)[35]	C	Australia [N]	1298	9-13	School children	Multivariate logistic regression

RCT, randomized controlled trial; IDEFICS, Identification and prevention of Dietary- and lifestyle-induced health EFfects In Children and infantS; AS!BC, Action Schools! British Columbia.

[a]Studies included in meta-analyses are in bold.

[b]Study design: [C] – Cross-sectional study; [L] – Longitudinal study; [RC] – Repeated cross-sectional study.

[c]Study area: [N] – National; [S] – State (e.g., in the US) or equivalent unit (e.g., province in China, Canada); [S*n*] – *n* states or equivalent units; [CT] – County or equivalent unit; [CT*n*] – *n* counties or equivalent units; [C] – City; [C*n*] – *n* cities.

[d]Sample age: Age in baseline year for longitudinal studies or mean age in survey year for cross-sectional studies.

3.2 | Study characteristics

Table 1 summarized the basic characteristics of the 47 included studies. All the studies were published between 2006 and 2018, comprising 39 cross-sectional studies, six longitudinal studies, and two studies that contained both study designs. The sample size in these studies ranged widely from 88 to 46 813. The majority of the studies was conducted in the United States (n = 20), followed by in Australia (n = 7), Canada (n = 7), Belgium (n = 2), Ireland (n = 2), New Zealand (n = 2), Portugal (n = 2), and one study in each of China, Denmark, Germany, Israel, and Spain. Twelve studies were conducted at a national level; four were conducted in one state (ie, subnational) and one study in multiple states; two were conducted at the county level, and the rest were at the city level (nine were conducted in more than one city).

3.3 | Measures of street connectivity

Street connectivity was either perceived or objectively measured by Geographic Information Systems (GIS) (Table S1). The perceived measures were included in the questionnaires of Neighborhood Environment Walkability Scale for Youth (NEWS-Y), Assessing Levels of Physical Activity environmental (ALPHA), Neighborhood Impact on Kids (NIK), and the International Physical Activity Prevalence Study. The most commonly used perceived measure was the NEWS-Y questionnaire, with a statement about street connectivity for participants to agree or not agree: “The street in my neighborhood does not have many cul-de-sacs, and there are many different routes for getting from place to place.”

More than half of the 36 GIS-based studies measured SID, ie, the number of street intersections within buffer zones centred on individual addresses or schools, with varying radii (from 0.25 to 8.05 km) and two major methods of measuring radii (ie, straight-line and road-network). The most commonly used buffer zone was a 1-km road-network buffer (n = 7), followed by 1-km straight-line (n = 4), 0.8-km straight-line (n = 4), 0.8-km road-network (n = 4), 1.6-km road-network (n = 4), 0.4-km straight-line (n = 3), 0.4-km road-network (n = 2), 2-km straight-line (n = 2), 2-km road-network (n = 2), 5-km straight-line (n = 2), and the others used in the only study. Other measures of street connectivity were also used, for example, the Boone-Heinonen–calculated alpha index, and the ratio of the observed to maximum possible route alternatives between intersections.

3.4 | Association between street connectivity and weight-related behaviours

Forty-four studies examined the association between SID and weight-related behaviours, including PA (n = 42), specifically overall PA (n = 15), moderate-to-vigorous PA (MVPA) (n = 13), active transport (n = 12), dog walking (n = 1), and walking (n = 1), as well as sedentary behaviours (n = 2) including one specifically measuring TV viewing (Table S1). Eighteen studies objectively measured adolescents' PA by requesting participants to wear an accelerometer, while 32 studies had participants perceive the PA level via questionnaires, self-reporting, and parents' estimation.

Four and six (of 15) studies measuring the overall PA reported negative and positive associations between street connectivity and PA, respectively, while the remaining studies did not report a significant association in their results. Three, six, and two (of 13) studies measuring MVPA reported negative, positive, and not significant associations between street connectivity and MVPA, respectively, with three studies reporting both negative and positive associations in different groups of participants. Greater street connectivity was also associated with dog walking,[27] walking,[31,20] and active transport to school,[4,30] while being negatively associated with sedentary time.[28]

3.5 | Association between street connectivity and weight-related outcomes

Fifteen studies measured weight-related outcomes, including BMI (n = 12), BMI *z*-score (n = 2), and weight status (n = 1). Three studies reported negative associations between street connectivity and weight-related outcomes: one study reported this association between the number of four-way intersections within a 800-m home straight-line buffer and the change in BMI *z*-score[7]; one found this association with girls' weight status only[25]; and another study reported this inverse relationship on the basis of both cross-sectional and longitudinal data.[47] Four studies reported no associations between street connectivity and BMI.

3.6 | Study quality assessment

Table S2 reported criterion-specific and global ratings from the study quality assessment. The included studies scored 6.42 of 14 on average, ranging from 4 to 9.

3.7 | Meta-analysis of associations between street connectivity and PA

The pooled OR (Figure 2) for the association between street connectivity and PA was 1.06 (95% CI, 1.02-1.09; I^2 = 87.1%). Although the funnel plot (Figure S1) showed slightly more studies located to the right side of the overall effect, there was no evidence of publication bias as neither Egger regression intercept test nor Begg rank correlation test was significant (1-tailed P = .05 and 1-tailed P = .21, respectively).

Subgroup analyses were conducted to assess the association between street connectivity and PA (Table 2). Studies with perceived street connectivity by children showed the highest pooled effect (OR = 1.13; 95% CI, 1.04-1.24; I^2 = 78.7%), while studies with measured street connectivity showed a marginally significant pooled effect of 1.03 (95% CI, 1.00-1.07; I^2 = 84.8%). Studies with reported street connectivity by parents had the lowest pooled effect (OR = 0.85; 95% CI, 0.47-1.52; I^2 = 86.8%). Those examining the association of street connectivity in residential neighbourhoods with PA showed a significant pooled effect (OR = 1.06; 95% CI, 1.01-1.10; I^2 = 87.6%), compared with the ones examining school neighbourhoods (OR = 1.28; 95% CI, 0.95-1.71; I^2 = 88.9%). Considering PA type, studies

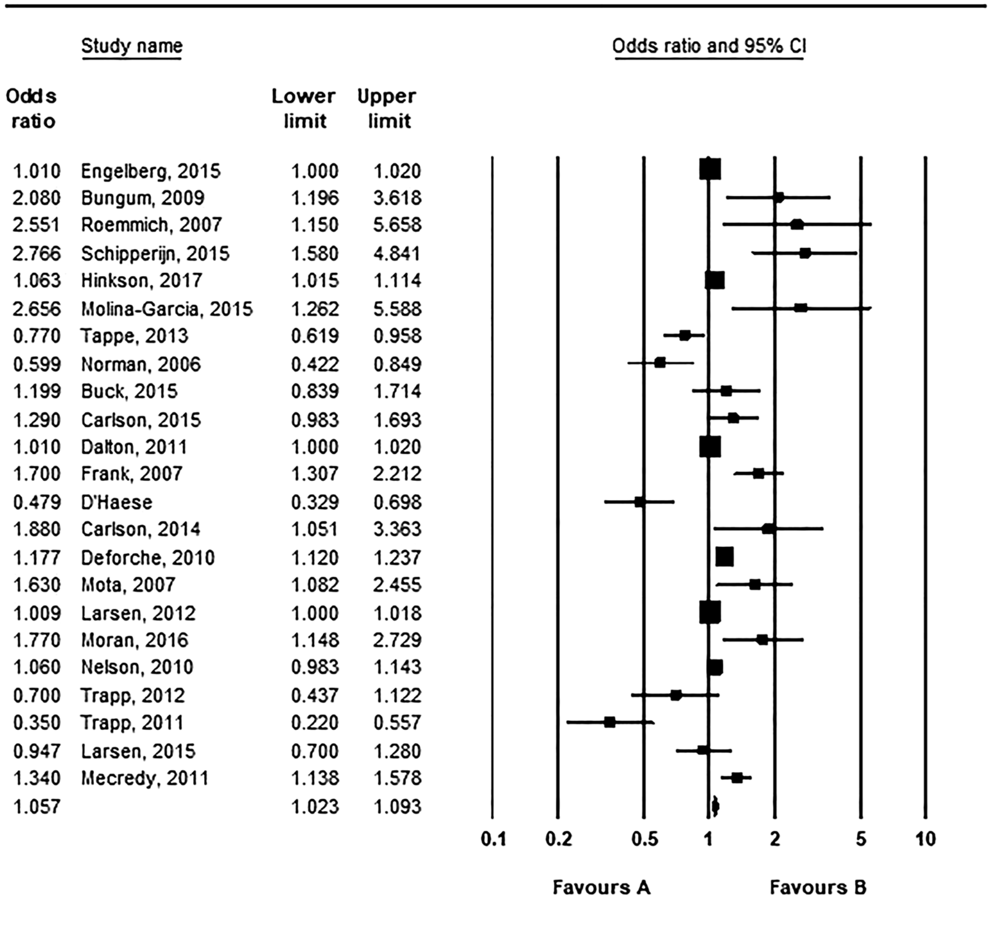

FIGURE 2 Pooled effect estimate for the association between street connectivity and weight-related behaviours

focusing on MVPA showed the highest pooled effect (OR = 1.33; 95% CI, 1.17-1.52; I^2 = 0%). No significant pooled effects were observed in other types of PA.

TABLE 2 Pooled effect estimates by subgroups of study characteristics

	N[a]	Pooled OR (95% CI)[b]	I^2, %
Methods of street connectivity measurement			
Objective	15	1.03 (1.00-1.07)	84.8
Perceived (by children)	5	1.13 (1.04-1.24)	78.7
Perceived (by parents)	3	0.85 (0.47-1.52)	86.8
Sites of street connectivity			
Home	20	1.06 (1.01-1.10)	87.6
School	3	1.28 (0.95-1.71)	88.9
Type of PA[c]			
ATS	9	1.07 (1.03-1.11)	87.9
MVPA	4	1.33 (1.17-1.52)	0.0
PA	6	0.77 (0.53-1.13)	92.5
Walk	4	1.07 (0.80-1.42)	82.9

Abbreviations: ATS, active transport to school; MVPA, moderate-to-vigorous physical activity; PA, physical activity.

[a]Number of studies included.

[b]Calculated by random effect models.

4 | DISCUSSION

In this study, we systematically reviewed 47 studies that assessed the association between street connectivity and weight-related behaviours and outcomes among children and adolescents. Mixed results were observed for this association among the included studies. Although more than half of the studies reported that higher street connectivity was associated with more PA and better weight status, other studies showed either opposite or null associations.

Our findings about the relationship between street connectivity and weight-related behaviours were consistent with a systematic review,[48] where the reported SID seemed to promote walking consistently. In this review, we identified 44 studies that analysed the association between street connectivity and weight-related behaviours, and measures of behaviours varied across those studies. PA and MVPA were most commonly measured, and the majority of the studies measuring them showed that higher access to SIDs could predict higher levels of PA and MVPA. This link is probable, since better street connectivity likely provides a more walkable environment, especially for children and adolescents.

Some studies found negative associations between street connectivity and children's PA/MVPA, and the reason might be that neighbourhoods with higher street connectivity may have fewer cul-de-sacs and thus be high-traffic areas, which are not suitable for children's outdoor activity.[49]

BMI and BMI *z*-score were the main weight-related outcomes analysed in the included studies. It is difficult to draw conclusions on its association with street connectivity, due to the limited number of available studies, although some studies did indeed find a negative relationship.[7,47] Several conceivable reasons may help explain the null findings for BMI. For instance, more walkable neighbourhoods may also provide greater access to food outlets, thereby offsetting benefits from increased PA.[26] However, on the other hand, food environments may also confound the observed negative association between street connectivity and weight status.[50-52] Besides, the home environment could be one of confounding factors, which may be more often associated with weight status than residential neighbourhood environment.[24] Other aspects of the neighbourhood built environment may also confound the association of interest.[53,54]

There were some limitations in the included studies that need to be acknowledged, which also suggest future research in several directions. First, the measurement of SID took place at only one scale in some studies or at multiple scales defined differently across studies, which has weakened the comparability among studies. Also, more measures of street connectivity and access to walkable streets should be used. Second, the majority of the studies included was cross-sectional with few longitudinal studies. The increasing use of the advanced spatial and big data approaches will lead to more frequent measurements of built environments for the longitudinal study design and the linkage to follow-up health data.[55-57] The testing of statistical power has also been suggested for longitudinal studies, so reasons for selecting or recruiting the number of people included or analysed should be presented.[58] Also, multiple measurements of street connectivity in those rapidly developed regions are needed to increase the reliability of exposure measurements. Third, confounding factors were differently controlled across studies, which may affect the results obtained. Fourth, the perceived street connectivity has almost been measured by traditional questionnaires, which, to some extents, reflected the perception of parents and may not be associated with children's activities. New technologies and approaches could be used to measure children's perception.[59] Finally, weight-related behaviours and outcomes (or their definitions) differed across studies, which limited the number of studies that could be included in the meta-analysis. All those differences in the measurement could lead to heterogeneity, which remained in our subgroup analyses (except for MVPA) and may also be from other potential sources (eg, differences in study design and population and methods of data collection).

5 | CONCLUSIONS

This review showed mixed findings, although a larger number of the included studies revealed a positive association between street connectivity and PA, and a negative association between street connectivity and weight-related outcomes. Note that higher street connectivity may only represent higher potential use instead of actual use; the latter needs to be measured by combining both objective and perceived measures. More longitudinal evidence is needed to strengthen the causality of this association. Research on the utilization of streets in the neighbourhood and the pathways from street connectivity to childhood obesity are needed to allow multiple stakeholders to design effective interventions and policies for preventing childhood obesity.

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CONFLICT OF INTEREST

No conflict of interest was declared.

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SUPPORTING INFORMATION

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

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