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Urban environment and obesity and weight-related behaviours in primary school children

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ABSTRACT

Background: Urban environments are characterised by many factors that may influence children's lifestyle and increase the risk of childhood obesity, but multiple urban exposures have scarcely been studied.

Objective: We evaluated the association between multiple urban exposures and childhood obesity outcomes and weight-related behaviours.

Methods: We conducted a cross-sectional study including 2213 children aged 9–12 years in Sabadell, Spain. We estimated ambient air pollution, green spaces, built and food environment, road traffic and road traffic noise at residential addresses through a total of 28 exposure variables in various buffers. Childhood obesity outcomes included body mass index (BMI), waist circumference and body fat. Weight-related behaviours included diet (fast food and sugar-sweetened beverage consumption), physical activity, sedentary behaviour, sleep duration and well-being. Associations between exposures (urban environment) and outcomes (obesity and behaviours) were estimated in single and multiple-exposure regression models and in a hierarchical clustering on principal components (HCPC) analysis.

Results: Forty percent of children were overweight or obese. In single exposure models, very few associations were observed between the urban exposures and obesity outcomes or weight-related behaviours after correction for multiple testing. In multiple exposure models, PM_{coarse}, denser unhealthy food environment and land use mix were statistically significant associated with childhood obesity outcomes (e.g 17.7 facilities/km^2 increase of unhealthy food environment (OR overweight/obesity status) = 1.20 [95% CI: 1.01; 1.44]). Cluster analysis identified 5 clusters of urban exposures. Compared to the most neutral cluster, the cluster with high air pollution, road traffic, and road noise levels was associated with a higher BMI and higher odds of overweight and obesity (β (zBMI) = 0.17, [95% CI: 0.01, 0.17]; OR (overweight/obesity) = 1.36, [95% CI: 0.99, 1.85]); the clusters were not associated with the weight-related behaviours.

Conclusions: This systematic study of many exposures in the urban environment suggests that an exposure pattern characterised by higher levels of ambient air pollution, road traffic and road traffic noise is associated with increased childhood obesity risk and that PM_{coarse}, land use mix and food environment are separately associated with obesity risk. These findings require follow-up in longitudinal studies and different settings.

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1. Introduction

Increasing trends of childhood obesity seem to have plateaued or even slightly decreased in high-income countries in the last decade, but levels are still alarmingly high, especially in Spain which has the second highest prevalence levels of childhood obesity in Europe ((NCD-RisC), 2017; de Bont et al., 2020a; WHO, 2018). Childhood obesity has been associated with type 2 diabetes mellitus, hypertension, obstructive sleep apnoea, dyslipidemia and mental health problems (Kumar and Kelly, 2017). Excessive weight status is a consequence of a chronic imbalance between excessive energy intake and/or reduced energy expenditure (Kipping et al., 2008; Trasande et al., 2010). The interaction of genetics, lifestyle behaviours and environmental exposures are likely to contribute to this imbalance (Kipping et al., 2008; Trasande et al., 2010). Additionally, the rapid growth of urban areas worldwide has greatly increased the levels of environmental stressors such as higher levels of air pollution, noise and lack of green spaces. This increasing degree of global urbanisation can influence personal behaviours of urban residents, such as physical activity levels and sedentary behaviour (Nieuwenhuijsen, 2016), and ultimately contribute to the energy imbalance (Gascon et al., 2016; Nieuwenhuijsen, 2016).

A number of studies have recently reported associations between increased levels of air pollution, road traffic, and traffic noise, and increased childhood growth and obesity (Christensen et al., 2016; de Bont et al., 2020b, 2019; Jerrett et al., 2010; Wang et al., 2020; Weyde et al., 2018). Increased levels of green spaces, access to facilities, more diversity of land use, and more walkable areas have been reported to be protective against obesity in children (de Bont et al., 2020b; Feng et al., 2010; Frank et al., 2019; Luo et al., 2020; Renalds et al., 2010). Most of these studies have reported single-exposure associations and have not systematically assessed associations for many urban exposures. To the best of our knowledge there have been only two studies that assessed the associations between multiple urban exposures and childhood obesity (Bloemsma et al., 2019; Vrijheid et al., 2020). The identification of combinations of exposures in urban environment that are more likely to be associated with childhood obesity may help policymakers and urban planners to identify which exposure clusters need to be addressed in order to make cities healthier and more liveable (Nieuwenhuijsen and Khreis, 2018)

The mechanisms underlying the effects of the multiple urban exposures and childhood obesity are still poorly understood. Air pollution may disrupt molecular mechanisms known to underlie obesity pathogenesis (Sun et al., 2009; Xu et al., 2010). Noise has been associated with stress hormones and sleep deprivation, which are associated with physical development in childhood, increasing the risk of overweight in children (Münzel et al., 2017; Nielsen et al., 2011; Pervanidou and Chrousos, 2011). Green spaces, built environment factors and road traffic may partly determine the levels of air pollution and noise and in turn affect the levels of obesity (Frank et al., 2019; Nieuwenhuijsen, 2016). Further, the urban environment may influence several weight-related behaviours including well established obesity risk factors such as diet, physical activity, sedentary behaviour, sleep duration and well-being (Kumar and Kelly, 2017). Poorer well-being may not be considered a direct weight-related behaviour, but poor mental health is associated with obesity and changes in diet and physical activity may be responsible for this (Liem et al., 2008). Better understanding of the associations between urban exposures with weight-related behaviours is important for the development of future community-level health promotion programs to improve healthy behaviours in the city, but there are only few studies on this in children. For instance, in adolescents and in adults, increasing levels of air pollution have been associated with increased fast food consumption and with decreased levels of physical activity (Chen et al., 2019; Wang et al., 2020), whereas higher green space exposure has been associated with increased levels of physical activity and improved quantity of sleep (Luo et al., 2020; Shin et al., 2020).

The aim of this study is to systematically evaluate the association of multiple urban exposures (air pollution, green spaces, built and food environment, road traffic, and road traffic noise) and their patterns, with childhood obesity outcomes and weight-related behaviours.

2. Methods

2.1. Study design and study population

We conducted a cross-sectional school-based study between October 2017 and January 2019 in the city of Sabadell, Spain (approximately 200,000 inhabitants) within the ECHOCAT (Urban built environment and childhood obesity in Catalonia) project. We aimed to recruit all children in the 4th, 5th and 6th year of primary school (between 9 and 12 years old) in Sabadell. Of the 37 Sabadell primary schools that were contacted, 30 schools agreed to join the study. Out of all children and their families contacted at these schools ($n = 3542$), 1970 (56%) agreed to participate. Participating schools were similar to the remaining schools in Sabadell in terms of urban exposure levels (i.e NO_2 levels [38.1 versus 39.8 $\mu g/m^3$, Kruskal-Wallis test, $p = 0.54$)], except for noise levels (60.1 versus 63.0 dB(A), $p = 0.02$). Additionally, we included children participating in the longitudinal INMA (INfancia y Medio Ambiente, Environment and Childhood) Sabadell birth-cohort study. In INMA, 778 pregnant women were recruited in the first trimester of pregnancy between 2004 and 2006, and were followed from then onwards (Guxens et al., 2012). In this study, we included the INMA children who participated in the follow-up visit at age 10–12 and attended Sabadell primary schools in the 4th, 5th and 6th years ($n = 481$) during the same period of the ECHOCAT study. Similar protocols for data collection, outcome assessment and exposure assessment were used in ECHOCAT and INMA. In both studies, all parents or tutors/guardians signed a consent form and the studies were approved by the Clinical Research Ethical Committee (ECHOCAT N° = 2016/6635/I, INMA N° = 2016/6708/I) of the IMIM-Parc de Salut MAR, Barcelona, Spain.

2.2. Childhood obesity outcomes

Child anthropometric measurements (height, weight, waist circumference and body fat percentage) were measured following the same standardized protocol in ECHOCAT and INMA at schools. All measurements were taken without shoes and in light clothing by specially trained personnel. Child height (nearest 0.1 cm) and weight (nearest 0.1 kg) were used to calculate age-and-sex specific BMI z-scores (zBMI, in standard deviation units) following the World Health Organization Growth Reference (de Onis et al., 2007). Children with a zBMI higher than +1 were defined as overweight including obesity, and children below this cut off were considered normal weight, including underweight. We focused on children with overweight rather than only children with obesity because the large number of children that have excess weight and are known to be at an increased risk of multiple adverse health outcomes. Additionally, waist circumference (nearest 0.1 cm) was measured at the high point of the iliac crest and with minimal respiration using an inelastic tape (model 201; SECA, Hamburg, Germany). Percentage body fat was measured using bioelectrical impedance analyses (TANITA DC-360 and Bodystat 1500 instruments were used in ECHOCAT and INMA, respectively). For INMA we calculated body fat percentage using validated bioimpedance formulas as these are validated for the Bodystat instrument (Clasey et al., 2011). For ECHOCAT we used the body fat percentage values directly obtained from the TANITA instrument (McCarthy et al., 2006), because the Clasey equation is not validated for this instrument. The values from the TANITA were highly correlated with the values from the Clasey equation (Pearson correlation $r_s = 0.94$). Finally, we obtained waist circumference and body fat percentage z-scores by calculating standardized residuals from a regression model of waist circumference and body fat percentage as dependent variable, with age, sex and study (ECHOCAT, INMA) as predictors (Eisenmann, 2008). Overall, the outcomes were highly correlated with each other, zBMI and waist circumference z-scores had a Pearson correlation of 0.86, and zBMI and body fat percentage z-scores of 0.79. Therefore, we decided to keep zBMI and overweight/obesity status (normal weight vs overweight/obesity) as our main outcome, and waist circumference and body fat percentage z-scores as sensitivity analyses. zBMI, waist circumference and bioimpedance measures are considered as markers of adiposity, intra-abdominal obesity and body composition, respectively (Moreno et al., 2011).

2.3. Weight-related behaviours

Weight-related behaviours including diet, physical activity, sedentary behaviour, and sleeping duration were collected from parents through questionnaires. Psychological well-being was collected directly from the children.

Data about dietary intake and dietary behaviours were obtained through a specific questionnaire and a modified version of a validated food-frequency questionnaire (FFQ) (Vioque et al., 2019). The food frequency questionnaire referred to the child intake in the previous year, and it was completed by the parents, and the responses were transformed to times/week of intake. We selected two items as indicators of unhealthy diet: fast food consumption in restaurants and consumption of sugar-sweetened beverages. The fast food consumption in fast food restaurants was obtained from this question "How often does your child eat fast food (eg. burger, french fries, hot dogs, pizza) in fast food restaurants?". From the FFQ we obtained the sugar-sweetened beverage consumption. Both variables were categorised (<1 time/week, ≥1 times/week) as studies suggests that more frequent users (more than once weekly) are at higher risk (Tambalis et al., 2018).

Minutes of physical activity per week were obtained through an adapted version of the Children's Leisure Activities Study Survey (CLASS) (Telford et al., 2005, 2004). We summed the total amount of time (in hours) of all physical activities performed in an average week. Additionally, we summed the total amount of time spent in vigorous physical activity hours/week. Since almost all activities had a metabolic equivalent of task (MET) score higher than 3, this can be considered as the total time spent in moderate-to-vigorous activity. Vigorous physical activity was defined as activities with a score higher than 6 obtained from of the Butte and Ridley compendium (Butte et al., 2018; Ridley et al., 2008). The physical activity variables were only obtained for the children participating in the ECHOCAT study.

Sedentary behaviour was obtained from self-reported information on screen time. Total screen time (hours/week) was calculated by summing the total duration of television and computer time in hours per week. Both television and computer duration was calculated as: total television/computer time = 5 × weekday television/computer time duration + 2 × weekend television/computer time duration.

Sleep duration (in hours/night) was calculated by subtracting the time the child woke up with the time the child went to bed and actually turned off the light during weekdays.

Psychological well-being was obtained through the KIDSCREEN-27 questionnaire that evaluates the health-related quality of life (Robitail et al., 2007). KIDSCREEN-27 questionnaire consists of 27 items related to physical well-being (5-item), psychological well-being (7-item), autonomy and parent relations (7-item), social support and peers (4-item), and school environment (4-item). We calculated the total score following the KIDSCREEN protocol (Robitail et al., 2007), by summing up all item responses (certain items were reversed according to the protocol). Lower values indicated poorer health-related quality of life.

2.4. Exposure assessment: the urban environment

A wide range of urban environment exposures were estimated using geographic information system (GIS) platforms, using protocols developed for the HELIX project (Nieuwenhuijsen et al., 2019; Robinson et al., 2018; Vrijheid et al., 2020). We estimated the urban environment in the following exposure groups: ambient air pollution, green spaces, built environment, food environment, road traffic, and road traffic noise. Data sources and time points are specified in Table 1. The exposures were estimated at the geocoded residential address of the children and were averaged over the year before the clinical examination.

The assessment of ambient air pollution included nitrogen dioxide (NO_2), nitrogen oxides (NO_x), particulate matter (PM) with an aerodynamic diameter of less than 10 μm (PM_{10}) and of less than 2.5 μm ($PM_{2.5}$), PM between 2.5 μm and 10 μm (PM_{coarse}), and absorbance of $PM_{2.5}$ (PM_{abs}) filters. We based the air pollution exposure assessments on the land-use regression (LUR) modelling approach developed in the European Study of Cohorts for Air Pollution Effects (ESCAPE) framework (Beelen et al., 2013; Eeftens et al., 2012). Following the ESCAPE guidelines, we applied temporal adjustment for the exposure level to each pollutant by combining the LUR spatial estimates at the geocoded address of the child and data obtained from the background routine monitoring stations in Sabadell. Specifically, we used the ratio of the concentration of the background monitor of each day of the study period and the annual average during 2009 (year of sampling campaign). We used the Catalunya model that (R^2) 62–76%% of the annual variation levels of the air pollutants in 2009.

For green spaces, we included green space availability and accessibility indicators. We followed the Positive health Effects of the Natural Outdoor Environment in Typical Populations in Different Regions in Europe (PHENOTYPE) study (Nieuwenhuijsen et al., 2014) to estimate the surrounding greenness (trees, shrubs, and parks) with the Normalized Difference Vegetation Index (NDVI). We obtained satellite data derived from the Landsat 4–5 Thematic Mapper (TM) with 30 m × 30 m resolution. We selected images of 2017 according to the following criteria: i) cloud cover less than 10%, ii) Standard Terrain Correction (Level 1 T) and iii) greenest period of the year (May-August). We estimated surrounding greenness within 100-m, 300-m, and 500-m buffers around each address. Additionally, we calculated the distance to the nearest major green spaces and the area of this space, considered as open areas more than 5000 m^2. Finally, we created a dichotomous variable to evaluate whether a major green space was available or not within a buffer of 300 m (approximately within 15 min' walk for children).

We calculated multiple built environmental factors from topological maps obtained from the municipality of Sabadell or from Europe-wide sources including NAVTEQ and Urban Atlas (Copernicus, 2020; HERE Global B.V., 2017). Population density was calculated as the number of inhabitants per square kilometres surrounding the children's home address (from 100 m × 100 m raster). Connectivity density was calculated as the number of street intersections inside 100-m and 300-m buffers, divided by the area (km^2) of each buffer. Two facility indexes were calculated: a) facility density was calculated as the number of facilities present divided by the area of the 300-m buffer: and b) Facility richness index was calculated as the number of different facilities types present divided by the maximum potential number of facility types specified, in a buffer of 300-m, giving a score of 0 to 1. Facilities included businesses, community services, educational institutions, entertainment, financial institutions, hospitals, parks and recreation, restaurants, shopping, and transport. Land use mix was obtained through the Shannon's Evenness Index (SEI). SEI was calculated by multiplying each proportion of land use type by its logarithm and dividing the sum of all land use type products by the logarithm of the total possible land use types within 300-m buffer. We developed an indicator of walkability, adapted from previous walkability indices (Duncan et al., 2011; Frank et al., 2006), calculated as the mean of the deciles of population density, connectivity density, facility richness index, and land use SEI within 300-m buffers, giving a walkability score ranging from 0 to 1. The accessibility of public transportation was measured by public bus transport lines and the amount of bus stops inside 100-m, 300-m, and 500-m buffers, divided by the buffer area.

Table 1
Data source and time period of the exposure assessment.

Exposure Group	Exposure variables	Units	Source	Time period
Air pollution	NO_2/NO_x/$PM_{2.5}$/PM_{10}/PM_{coarse}/PM_{abs}	$\mu g/m^3$ (for $PM_{abs} = 10^{-5}\ m^{-1}$)	ESCAPE LUR	2009
Green spaces	NDVI (buffers of 100, 300 and 500 m)	0 to 1	Landsat 4–5 TM	2017
	Straight line distance to nearest major spaces*	m	Urban atlas	2012
	Distance and size of closest major space*	m	Urban atlas	2012
	Is there a major space within 300 m?	yes/no	Urban atlas	2012
Built environment	Population density*	people/km^2	GHSL	2015
	Street connectivity (buffers 100 and 300 m)*	intersections/km^2	NAVTEQ	2012
	Land use Shannon's Evenness Index (within 300 m)	0 to 1	Urban atlas	2012
	Facility density (within 300 m)	Facilities/km^2	NAVTEQ	2012
	Walkability index (within 300 m)	0 to 1	GHSL, NAVTEQ, Urban atlas	2012–2015
	Accessibility (bus stops with buffers of 100, 300 and 500 m)*	n° bus stops/km^2	Sabadell municipality	2014
Food environment	Unhealthy food environment	Unhealthy facilities/km^2	NAVTEQ	2012
Road traffic	Traffic load all roads (within 100 m)	vehicles/day m	GENCAT	2007
	Traffic load in the nearest major road (within 100 m)*	vehicles/day m	GENCAT	2007
	Traffic density	vehicles/day	GENCAT	2007
	Inverse distance nearest road	m^{-1}	NAVTEQ	2012
Road traffic noise	L_{den} and L_n	dB(A)	GENCAT	2012

Abbreviations: ESCAPE, European Study of Cohorts for Air Pollution Effects; ESM2p5m, European Settlement Map 2017; GENCAT, Generalitat of Catalonia; GHSL, Global Human Settlement Layer; LUR, Land Use Regression; Lden, annual average of day, evening and night noise levels; Ln, annual average night noise levels; Navteq: ESRI Street Map for Mobile Navteq 2012; NDVI, Normalized Difference Vegetation Index; NO_2, nitrogen dioxide; NO_x, nitrogen oxides; $PM_{2.5}$, particulate matter with an aerodynamic diameter of less than 2.5 μm; PM_{10}, particulate matter with an aerodynamic diameter of less than 10 μm; PM_{coarse}, particulate matter with an aerodynamic diameter of between 2.5 than 10 μm; $PM_{2.5abs}$, absorbance of $PM_{2.5}$ filters; TM, Thematic Mapper.

* The following exposures were categorized below and above the median because they did not achieve normality for imputation: straight line distance to a green space, area of the nearest green space, population density, bus stops (100 m, 300 m and 500 m buffer). Road traffic load in the nearest major road was categorized in three categories (0-values equal to 0, 1-below the median, 2-above the median).

We created an unhealthy food environment index based on the NAVTEQ database (Copernicus, 2020). This indicator equals the number of unhealthy facilities present divided by the area of the 300-m buffer (number of facilities/km^2). Among the 100 different subcategories of facilities in the NAVTEQ database we selected the subcategories related to unhealthy food (petrol/gasoline Station, bar or pub, coffee shop, restaurant, convenience store, shopping malls). Higher values indicate more availability of different unhealthy facilities.

Road traffic indicators were calculated from traffic road network maps following the ESCAPE protocol (Beelen et al., 2013; Eeftens et al., 2012). We estimated the following indicators: traffic load on all roads, traffic load on the major road within 100 m, traffic density on nearest road, and inverse distance to nearest major road.

Road traffic noise levels were derived from noise maps produced in each local municipality (including Sabadell) under the European Noise Directive (European Commission, 2002). We obtained two road traffic noise variables: a) Lden was calculated as the annual average sound pressure level of a 24-h periods (day, evening, night); and b) Ln was calculated as the annual average sound pressure level of the night period.

2.5. Covariates

Information on parental sociodemographic factors were collected by children's parents through questionnaires. Covariate information included parental education (primary education or lower, secondary education, university education or higher), occupation (employed, others), country of birth (both parents native, none or one native parents), maternal household economy (living comfortably, doing alright, just about getting by, finding it quite/very difficult), maternal smoking status (non-smoker, ex-smoker, smoker), maternal BMI (kg/m^2), and the number of siblings (no siblings, 1 sibling, $\geq$2 siblings). Additionally, we estimated a deprivation index to account for area-level SES (Ministry of Public Works, 2015). The deprivation index was estimated at census track and was based on 5 socioeconomic indicators: % of unemployed population, % of unemployed youth population, % of eventual employment, % of unqualified employed persons and % of population without studies. The deprivation index was stratified in quintiles based on the Spanish population, where the lowest quintiles are the children living in the less deprived areas. Data was obtained from the Spanish Statistical office of 2001 (Instituto Nacional de Estadística, 2001).

2.6. Statistical analyses

2.6.1. Multiple imputations

Before imputation of missing values, we transformed all skewed exposures, weight-related behaviours and covariate variables to achieve normality; variables were categorized if normality was not achieved. We applied chained equations to impute all exposures, weight-related behaviours and covariate missing values (White et al., 2011). Physical activity was imputed for the whole INMA study sample. We imputed 20 datasets and we restricted the number of predictors in the imputation models to fewer than 25 variables while ensuring that all outcomes were considered as predictors (van Buuren, 2018). After imputation, we standardized all continuous exposure variables by the interquartile range (IQR). The following exposures were categorized below and above the median because they did not achieve normality for imputation: straight line distance to a green space, area of the nearest green space, population density, bus stops (100 m, 300 m and 500 m buffer). Traffic load in the nearest major road was categorized in three categories (values equal to 0, below and above the median). We further categorized the well-being outcome for imputation; we created a dichotomous variable with children below and above the median KIDSCREEN score (poorer vs. better well-being). In the analyses described below, results from each imputed dataset were combined using Rubin's rules.

2.6.2. Statistical models

For descriptive purposes, we first explored the associations between weight-related behaviours (fast food consumption in restaurants, sugar-sweetened beverage consumption, total and vigorous physical activity duration, screen time, sleep duration and psychological well-being) with the dichotomous outcome overweight/obesity status (normal weight vs.

overweight/obesity) by using a logistic regression models adjusting for study, age, sex, maternal education, and area-level SES. Then, we performed generalised additive models (GAMs) with the R package 'mgcv' to assess departures from linearity in the relationship between selected urban exposure and each outcome (we selected the urban exposures included for the multiple exposure models below). Because almost all GAMs showed evidence of linearity as indicated by effective degrees of freedom close to 1 (Figure S2/S3), we modelled all exposure variables as continuous variables in subsequent analyses, assuming linear associations. Next, to assess the associations between the urban exposures and childhood obesity outcomes and weight-related behaviours, we applied linear regression models for the continuous outcome variables (zBMI, waist circumference and body fat percentages z-scores, total and vigorous physical activity, screen time and sleep duration) and logistic regression models for the dichotomous outcome variables (overweight/obesity status, fast food consumption, sugar-sweetened beverage consumption, and psychological well-being). We applied a three stage analyses strategy in the following order: an exposure wide association study (ExWAS) to screen all exposure-outcome associations, a multiple exposure model to evaluate possible confounding between the multiple urban exposures, and a hierarchical clustering on principal components (HCPC) analyses to capture patterns of the urban environment.

2.6.3. Single exposure analysis

We applied an ExWAS analyses to screen all possible individual exposure-outcome associations (Agier et al., 2016). This model relies on independent regression models to estimate the association between each exposure variable with each outcome, adjusting for potential confounders (see Section 2.6.6). We corrected the p-values thresholds to account for multiple hypothesis testing using a family-wise error rate correction (5% divided by the effective number of tests) (Li et al., 2012). The multiple testing corrected p-value threshold was 0.003.

2.6.4. Multiple exposure models

We applied multiple exposure models to evaluate the stability of the exposure-health associations by assessing possible confounding between the urban exposures. We selected one indicator within each exposure group which are the most common indicators in the literature: NO_2 (air pollution), NDVI + 300 m (green spaces), land use mix (built environment), unhealthy food environment, traffic density, and Lden (road traffic noise). Further, we added any other exposure that was significant at the p-value 0.05 level in the single exposure analysis. We selected the confounders for each urban exposure individually in the directed acyclic graphs (DAG) (Figure S1). In this DAG, green spaces, built environment factors, food environment, and road traffic are part of the urban design and may determine the levels of air pollution and road traffic noise in the city, and may thus be on the causal pathway between the urban design indicators and childhood obesity outcomes. Hence, the urban design indicators can be considered mutual confounders between each other, and are considered confounders between air pollution, road traffic noise and the childhood obesity outcomes and weight-related behaviours. Air pollution and road traffic noise are also considered as mutual confounders. In addition to our DAG-based multiple exposure models, we also constructed one model with all exposures together, recognising that the DAGs may be based on unverifiable assumptions.

2.6.5. Hierarchical clustering on principal components (HCPC)

We applied a HCPC analyses to classify children into clusters with similar urban exposures patterns. We performed the HCPC analyses on a reduced exposure dataset including only the continuous exposure variables (N = 20). Previously, a study in Sabadell found that children from higher area-level SES were associated with higher levels of air pollution, noise, traffic, and lower levels of green spaces (Robinson et al., 2018). Thus, SES may play an important role in the association between the urban exposure patterns and childhood obesity outcomes and weight-related behaviours. We therefore standardized all exposure variables by the mean within each quintile of the deprivation index before running the HCPC; Thus, the standardized exposures explore gradients in the particular exposure among individuals with a similar deprivation index.

We applied first a principal component analyses (PCA) to reduce the dimension of the data and selected the number of components that explained at least 80% of the variance in the data. We then applied an ascending hierarchical classification (AHC) to identify clusters of exposure based on the components obtained from the PCA. We applied AHC after the PCA, rather than directly to the original dataset, because the PCA removes noise in the data and results in more stable clustering analysis (Husson et al., 2017). We selected the numbers of clusters by applying the Ward's criterion based on the decomposition of the total inertia (i.e., total variance) in between- and within-group variance. The Ward's method consists in aggregating two clusters such that the growth of the within-inertia, characterizing the homogeneity of a cluster, is minimum (Husson et al., 2017) (supplemental Figure S4). The identified clusters were used in the regression models as an independent variable.

2.6.6. Confounder selection

All above models were adjusted for a common set of confounders. We selected the potential confounders based on the DAG to minimize overadjustment bias (Figure S1). The following variables were identified: study design, parental education, paternal occupation, and parental country of birth, maternal household economy, maternal smoking status, maternal BMI, the number of siblings, and area-level SES.

2.6.7. Sensitivity analyses

We performed sensitivity analyses to assess the robustness of our results based on our single exposure models: (a) in order to evaluate the role of SES in the associations between urban exposures and zBMI, we evaluated how the removal of individual- and area-level SES variables affected the main effect estimates; (b) to evaluate the effect of standardizing the urban exposures by SES, we evaluated the associations between the standardized continuous exposures and zBMI; and, (c) the models with zBMI as an outcome were additionally adjusted for physical activity and diet consumption, whereas the models with weight-related behaviours as outcome were adjusted for zBMI. We did not include these in the main models as they may act as mediators of some exposures rather than as confounders. (d) As children spend a large amount of time at schools, we evaluated the associations between the urban exposures estimated at the schools and zBMI. The exposures at schools were only available for the ECHOCAT children. (e) Gender differences may exist in the use of the urban environment and in weight-related behaviours; we evaluated the effect modification of sex by introducing an interaction term into the model and evaluating the p-value for interaction with the likelihood ratio test. For this sensitivity analysis, we applied single exposure associations selecting one urban indicator within each exposure group. (f) to evaluate the quality of the imputation, we compared the distribution of the covariates in the imputed and non-imputed dataset, and we repeated the single exposure analyses using zBMI as an outcome only in the complete case dataset.

3. Results

3.1. Study population

The study population included 2213 children, 1732 (78.3%) from ECHOCAT and 481 (21.7%) from INMA (Figure S5). Children from both studies had similar overweight and obesity levels, and showed similar weight-related behaviours (Table S1). The INMA study included more boys, children that were slightly older, and parents with slightly lower SES levels, than the ECHOCAT study. The children from both studies were on average 10.8 years old at baseline and 52.1% were girls (Table 2). The prevalence of overweight including obesity was 39.9%. Boys were more likely to have overweight/obesity than girls (42.2% vs.

Table 2
Characteristics of the included study population by overweight/obesity status (N = 2213).

	Normal weight [N = 1340 (60.6%)]	Overweight/ obesity [N = 873 (39.6%)]	Odds Ratio[1] (95CI)	Missing rate
Study design				0 (0.00%)
ECHOCAT	1057 (61.0%)	675 (39.0%)	ref	
INMA	283 (58.8%)	198 (41.2%)	1.07 (0.86; 1.33)	
Age at baseline, years	10.8 (0.8)	10.7 (0.8)	0.94 (0.83; 1.07)	0 (0.00%)
Sex				0 (0.00%)
Male	613 (57.8%)	447 (42.2%)	ref	
Female	727 (63.1%)	426 (36.9%)	0.80 (0.67; 0.95)	
Anthropometric measures:				
Age-sex zBMI score, SD	−0.1 (0.8)	1.8 (0.6)	–	0 (0.00%)
Waist circumference z-score, SD	−0.7 [−0.9; −0.3]	0.8 [0.3;1.5]	–	7 (0.32%)
Body fat (%) z-score, SD	−0.6 [−1.0; −0.2]	0.8 [0.4;1.4]	–	7 (0.32%)
Weight-related behaviours:				
Fast food consumption in restaurants, category				380 (17.2%)
<1 times/week	999 (62.2%)	607 (37.8%)	ref	
≥1 times/week	118 (52.0%)	109 (48.0%)	1.43 (1.08; 1.89)	
Sugar-sweetened beverage consumption, category				135 (6.10%)
<1 times/week	816 (62.6%)	487 (37.4%)	ref	
≥1 times/week	447 (57.7%)	328 (42.3%)	1.14 (0.94; 1.37)	
Physical activity duration, hours/week	13.5 [9.5; 18.8]	13.0 [8.9; 19.2]	1.00 (0.98; 1.01)	626 (28.3%)
Vigorous physical activity duration, hours/week	7.5 [4.0; 11.5]	7.0 [4.0; 11.5]	0.99 (0.97; 1.00)	621 (28.1%)
Screen time, hours/ week	11.2 [7.3; 16.3]	13.0 [8.8; 18.5]	1.02 (1.01; 1.03)	172 (7.8%)
Sleep duration during weekdays, hours/day	9.6 (0.6)	9.5 (0.6)	0.81 (0.70; 0.93	160 (7.2%)
Kidscreen-27 well-being, category				
Poorer well-being	600 (56.1%)	469 (43.9%)	ref	9 (0.4%)
Better well-being	734 (64.7%)	401 (35.3%)	0.72 (0.60; 0.85)	
Socioeconomic characteristics:				
Area socioeconomic status, quintiles				0 (0.0%)
First (least deprived)	645 (68.7%)	294 (31.3%)	ref	
Second	199 (55.1%)	162 (44.9%)	1.65 (1.28; 2.13)	
Third	287 (56.5%)	221 (43.5%)	1.54 (1.22; 1.93)	
Fourth	166 (51.9%)	154 (48.1%)	1.76 (1.34; 2.31)	
Fifth (most deprived)	43 (50.6%)	42 (49.4%)	1.90 (1.20; 3.00)	
Mother occupation, %				127 (5.7%)
Employed	1034 (61.8%)	638 (38.2%)	ref	
Other	232 (56.0%)	182 (44.0%)	1.03 (0.82; 1.31)	
Mother education, %				61 (2.8%)
Primary education or lower	177 (54.0%)	151 (46.0%)	ref	
Secondary education	567 (56.5%)	436 (43.5%)	0.99 (0.76; 1.28)	
University education or higher	559 (68.1%)	262 (31.9%)	0.69 (0.52; 0.92)	
Maternal household economy, %				178 (8.0%)
Living comfortably	246 (66.1%)	126 (33.9%)	ref	
Doing alright	543 (62.6%)	325 (37.4%)	0.98 (0.75; 1.27)	
Just about getting by	369 (57.6%)	272 (42.4%)	1.09 (0.82; 1.46)	
Find it quite/very difficult	81 (52.6%)	73 (47.4%)	1.28 (0.85; 1.94)	
Mother BMI, kg/m^2	23.0 [21.1; 25.2]	24.7 [22.2; 28.1]	1.60 (1.44; 1.78)	185 (8.4%)
Maternal smoking				168 (7.6%)
Non-smoker	554 (63.1%)	324 (36.9%)	ref	
Ex-smoker	408 (60.3%)	269 (39.7%)	1.11 (0.9; 1.37)	
Smoker	285 (58.2%)	205 (41.8%)	1.13 (0.9; 1.43)	
Parental country of birth, %				383 (17.3%)
Both parents native	928 (61.7%)	577 (38.3%)	ref	
None or one native parents	183 (56.3%)	142 (43.7%)	1.09 (0.85; 1.38)	
Father occupation, %				236 (10.7%)
Employed	1071 (62.2%)	650 (37.8%)	ref	
Other	132 (51.6%)	124 (48.4%)	1.38 (1.05; 1.82)	
Father education, %				208 (9.4%)
Primary education or lower	211 (52.9%)	188 (47.1%)	ref	
Secondary education		425 (40.9%)		

(continued on next page)

Table 2 (*continued*)

	Normal weight [N = 1340 (60.6%)]	Overweight/ obesity [N = 873 (39.6%)]	Odds Ratio[1] (95CI)	Missing rate
	614 (59.1%)		0.89 (0.68; 1.16)	
University education or higher	395 (69.7%)	172 (30.3%)	0.71 (0.51; 0.98)	
Siblings, %				159 (7.2%)
No siblings	269 (55.3%)	217 (44.7%)	ref	
1 Sibling	766 (62.8%)	453 (37.2%)	0.78 (0.62; 0.98)	
≥2 Siblings	217 (62.2%)	132 (37.8%)	0.78 (0.58; 1.04)	

Values are mean (Standard deviation (SD)) for continuous normal distributed variables, median (interquartile range) for continuous non-normal distributed variables, and percentage for categorical variables.

[1] logistic regression was assessed individually for each variable adjusting by study design, sex, age, maternal education and area-level SES.

36.9%). Further, we observed that higher consumption to fast food restaurants and increased levels of screen time were associated with a higher odds of overweight or obesity (odds ratio (OR) [high vs. low fast food in restaurants consumption] = 1.43, [95% confidence interval (CI): 1.08, 1.89]; OR [for each 1 h/week increase in screen time] = 1.02, [95 %CI: 1.01, 1.03]). Increased sleep duration during weekdays and better well-being were associated with a lower odds of overweight or obesity (OR [for each 1 h/day increase in sleep duration during weekdays] = 0.81, [95 %CI: 0.70, 0.93]; OR (better vs. poorer well-being) = 0.72, [95 %CI: 0.60, 0.85]). Higher maternal BMI, and lower parental individual and area level SES were associated with higher levels of overweight/ obesity (Table 2).

3.2. Exposure levels and distributions

Distributions of the urban exposures are shown in Table S2. We observed a clear gradient in the distribution of the urban exposures across the area-level SES quintiles (Table S2). In comparison with children living in the least deprived area, children living in the most deprived area were exposed to lower levels of air pollution, facility density, traffic load and road traffic noise, and to higher levels of green spaces, connectivity within 100-m, and land use mix. Pearson correlations (r_s) of all continuous environmental factors are shown in Figure S6. Air pollution exposures were negatively correlated with green spaces exposures (r_s ranging from −0.4 to −0.7) and positively with most built environmental factors ($r_s = -0.0$ to $+0.4$), unhealthy food environment ($r_s = +0.2$ to $+0.3$), road traffic indicators ($r_s = +0.0$ to 0.5), and road traffic noise ($r_s = +0.3$ to $+0.5$). Green spaces exposures were negatively correlated with built environmental factors ($r_s = -0.0$ to -0.6), food environment ($r_s = -0.3$ to -0.4), road traffic indicators ($r_s = -0.0$ to -0.2) and road traffic noise ($r_s = -0.1$ to -0.2). Overall, built environmental factors showed weak or moderate positive correlations with each other, and positively correlations with unhealthy food environment ($r_s = +0.2$ to $+0.4$). Road traffic indicators was positively correlated with road traffic noise levels ($r_s = +0.0$ to $+0.4$).

3.3. Single and multiple exposure associations with childhood obesity outcomes

In single exposure models, only PM_{coarse} was associated with an increase in child zBMI score at a $p < 0.05$ level (beta (β) = 0.05per 1.8 μg/m^3 increase in PM_{coarse}; 95% CI: 0.00, 0.10) (Fig. 1 and S7, and Table S3), but this association did not pass the multiple testing corrected p-value threshold of 0.003. There were some tendencies for proximity and size of green spaces and higher density of bus stops in 500 m to be associated with lower zBMI (β (proximity green spaces) = −0.04, [95% CI: −0.14, 0.06]; β (size green spaces) = −0.07, [95% CI: −0.17, 0.03]; β (bus stops + 500 m) = −0.07, [95% CI: −0.17, 0.03];) and the different air pollutants, unhealthy food environment and road traffic noise with higher zBMI [(β (PM_{10}) = 0.03, [95% CI: −0.02, 0.09]; (β (food environment) = 0.04, [95% CI: −0.04, 0.11]; β (Lden) = 0.06, [95% CI: −0.00, 0.12])], but none passed the 0.05p-value (Fig. 1 and S7, and Table S3). We did not observe a clear trend for NDVI, built environment factors and road traffic. Similar findings were obtained using the dichotomous overweight/obesity status variable, and for waist circumference and body fat percentage z-score (Fig. 1 and S7, Table S3).

In the multiple exposure models, we observed that the effect estimates for zBMI and overweight/obesity status remained mostly similar after adjusting by other urban exposures (Fig. 2). PM_{coarse} remained associated with zBMI after adjusting for multiple exposures (beta (β) = 0.06 per 1.8 μg/m^3 increase in PM_{coarse}; 95% CI: 0.00, 0.12) (Fig. 2). Notable, the associations between land use mix and unhealthy food environment and overweight/obesity status became stronger and statistically significant at a p-value level of 0.05 (0.2 units increase of land use mix (OR) = 1.30 [95% CI: 1.01; 1.69]; and 17.7 facilities/km^2 increase of unhealthy food environment (OR) = 1.20 [95% CI: 1.01; 1.44]) (Fig. 2). Unhealthy food environment also showed associations with waist circumference z-scores (β = 0.09 [95% CI: 0.01; 0.17]) and zBMI (borderline statistical significance; β = 0.09 [95% CI: −0.01; 0.18]) in the multiple exposure models. Estimates from models evaluating all exposures together (Fig. 2) were essentially the same as those from the multiple exposure models.

3.4. Single and multiple exposure associations with weight-related behaviours

None of the associations between urban exposures and weight-related behaviours were statistically significant after correction for multiple testing (Figure S8a/S8b/S9 and Table S4). However, some associations were observed at $p < 0.05$ level related with sugar-sweetened beverage consumption: greater density of bus stops and traffic on major roads were associated with a higher odds of drinking sugar-sweetened beverages, and NDVI with a lower odds. In the multiple exposure models, the effect estimates of the weight-related behaviours remained mostly similar to those in the single exposure analyses. However, some associations became statistically significant at a p-value level of 0.05 (Figure S10): land use mix was associated with an increase in screen time use (β = 1.25 h/wk; 95% CI: 0.22, 2.27), and NO_2 exposure was associated with poorer well-being (OR = 0.82, [95% CI: 0.70, 0.96]). Full multiple exposure models including all exposures together (Figure S10) were essentially the same as those from the multiple exposure models.

3.5. Cluster analyses

After standardizing the urban exposures by area-level SES, we obtained 5 different patterns of the urban environment in the cluster analyses (Fig. 3). Cluster 1 represented very high levels of green spaces and lower levels of air pollution, built environment characteristics, road traffic and road traffic noise levels. Cluster 2 was similar to cluster 1, but the exposure levels were closer to the overall mean. Cluster 3 represented approximately the overall mean of all the exposures and was considered as our reference category. In figure S11, we specified the deviation of each urban exposure concentration level compared with cluster 3. Cluster 4 represented higher levels of built environmental factors such as facility density and unhealthy food density. Finally, cluster 5 represented very high levels of air pollution, road traffic and

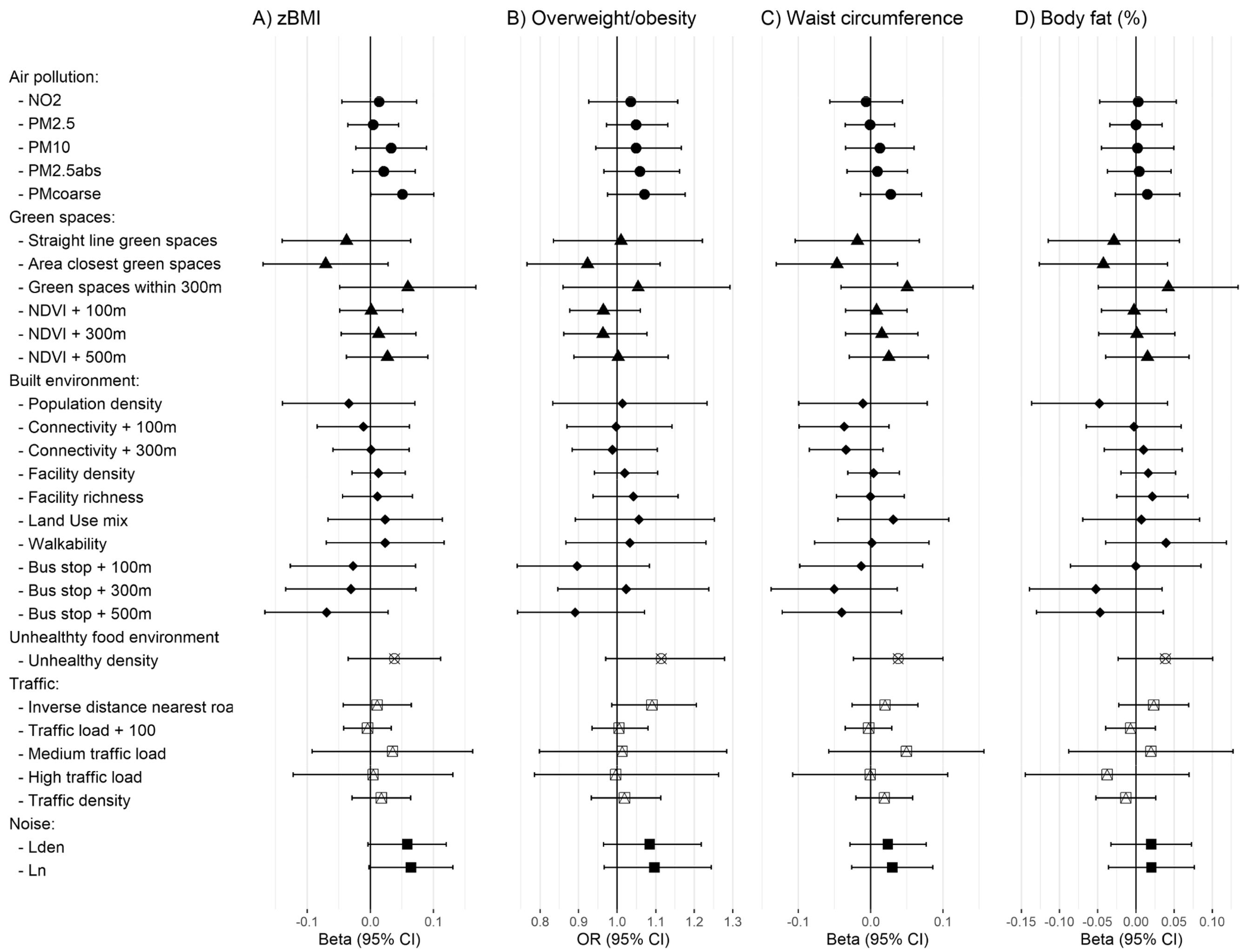

Fig. 1. Association between the urban environment and childhood obesity outcomes in single-exposure ExWAS model (N = 2213). Beta estimates and ORs for all exposures are shown in Table S3. Note: beta coefficient for change in zBMI and OR for overweight/obesity status is compared with reference category (normal weight) for the categorical variables. For continuous variables, beta estimates and OR are calculated per interquartile range increase in exposure. Models were adjusted by study design, maternal and paternal education, paternal occupation, occupation, and parental country of birth, maternal household economy, maternal smoking status, maternal BMI, the number of siblings, and area-level SES. Abbreviations: Lden, annual average of day, evening and night noise levels; Ln, annual average night noise levels; NDVI, Normalized Difference Vegetation Index; NO_2, nitrogen dioxide; NO_x, nitrogen oxides; $PM_{2.5}$, particulate matter with an aerodynamic diameter of less than 2.5 µm; PM_{10}, particulate matter with an aerodynamic diameter of less than 10 µm; PM_{coarse}, particulate matter with an aerodynamic diameter of between 2.5 than 10 µm; $PM_{2.5abs}$, absorbance of $PM_{2.5}$ filters; age-and-sex body mass index z-score, zBMI.

road traffic noise. Both cluster 4 and 5 had slightly lower levels of green spaces than cluster 1 and 2 but similar to cluster 3. We observed that cluster 5 was associated with higher zBMI and higher odds of overweight or obesity (β = 0.17, [95% CI: 0.01, 0.34]; OR (borderline statistical significance overweight/obesity vs. normal weight) = 1.36, [95% CI: 0.99, 1.85]), in comparison with cluster 3 (Table 3). We did not observe any significant associations between the different clusters and the weight-related behaviours (Table 3)

3.6. Sensitivity analyses

The effects estimates changed substantially after adjusting for SES variables, especially when we added area-level SES in the models (Table S5). We further observed that standardizing or adjusting by area-level SES did not change the results of the single exposure analyses (Table S6). Finally, we observed no changes in the effect estimates for zBMI after adjusting by diet (fast food and sugar-sweetened beverage consumption) or physical activity (Table S7), nor did we observe changes in the effect estimates of the weight-related behaviours after adjusting by zBMI (results not shown). Most of the effect estimates between the urban exposures estimated around schools and zBMI in the ECHOCAT children remained similar in direction as in the main analyses, with the exception of a higher level of connectivity around schools associated with a lower zBMI (Table S8). Child sex did not modify the associations between the multiple urban exposures and childhood obesity outcomes and weigh-related behaviours (Table S9). We observed similar distribution of the covariates in the non-imputed and imputed dataset (Table S10), and in the complete case-analyses the associations did not change notably (Table S11).

4. Discussion

In this study we evaluated systematically the associations between multiple urban exposures and childhood obesity outcomes and weight-related behaviours. We found weight-related behaviours, such as consumption of fast food in restaurants, screen-time, and sleep duration, to be associated with childhood overweight/obesity. In single and multiple exposure models there were few associations between urban environment exposures and the obesity outcomes or the weight-related behaviours. Exceptions were an association between higher PM_{coarse} levels and

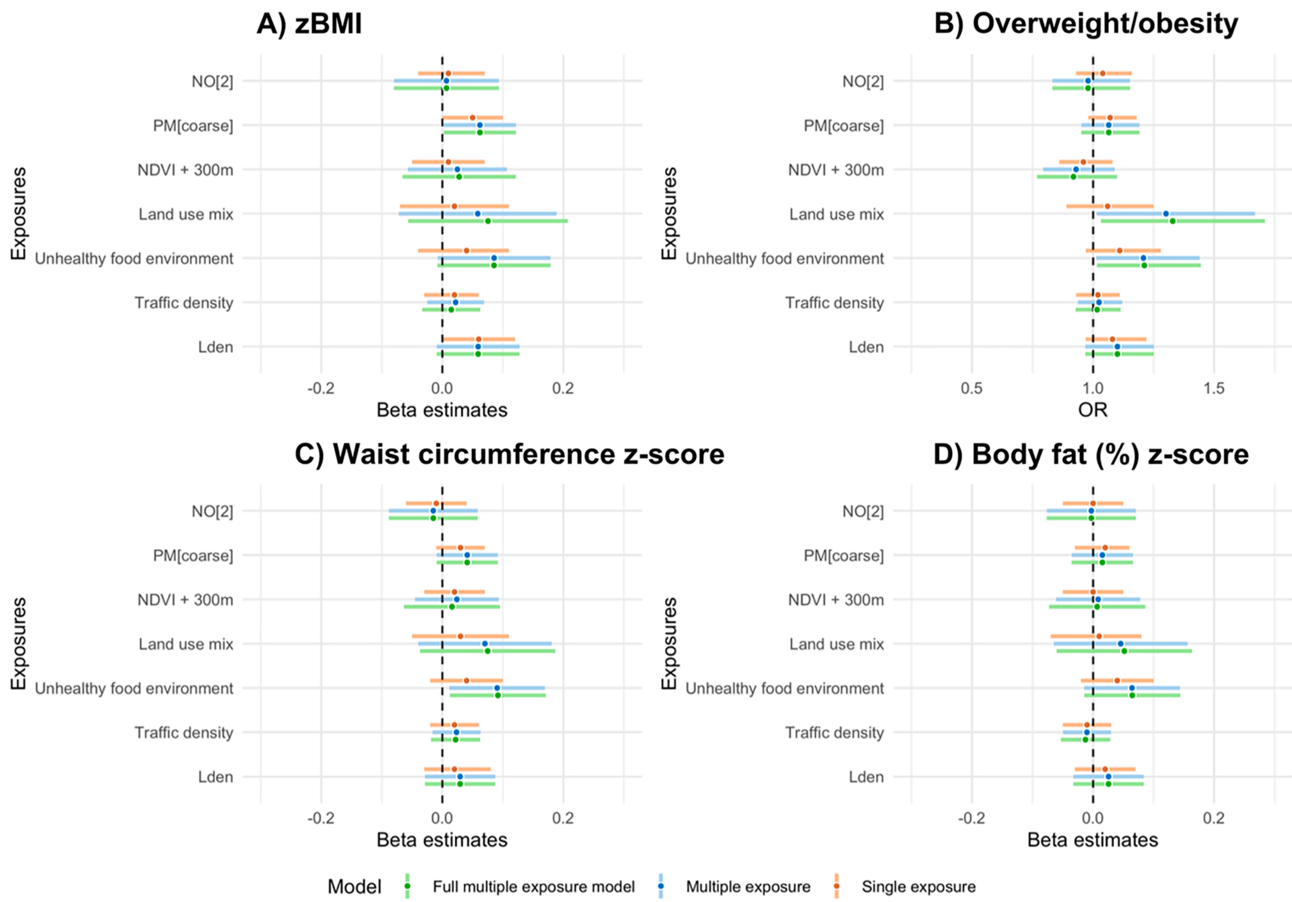

Fig. 2. Associations between urban environment and childhood obesity outcomes in multiple exposure models (N = 2213). Beta estimates for change in zBMI, waist circumference and body fat (%) z-scores, and OR for overweight/obesity status are compared with reference category (normal weight) for the categorical variables. The beta estimates and OR are calculated per interquartile range increase in exposure. Abbreviations: Lden, annual average of day, evening and night noise levels; Lden, annual average day-evening-night noise levels; NDVI, Normalized Difference Vegetation Index; NO_2, nitrogen dioxide; age-and-sex body mass index z-score, zBMI. Multiple exposure models for NO_2, PM_{coarse} and Lden were adjusted for NO_2, NDVI, land use mix, unhealthy food environment, road traffic density, Lden, design, maternal and paternal education, paternal occupation, occupation, and parental country of birth, maternal household economy, maternal smoking status, maternal BMI, the number of siblings, and area-level SES. Multiple exposure models for NDVI + 300 m, land use mix, unhealthy food environment and traffic density were adjusted for NDVI, land use mix, unhealthy food environment, road traffic density, design, maternal and paternal education, paternal occupation, occupation, and parental country of birth, maternal household economy, maternal smoking status, maternal BMI, the number of siblings, and area-level SES. Full multiple exposure model (including all exposures simultaneously): NO_2 or PM_{coarse}, NDVI, land use mix, unhealthy food environment, road traffic density, Lden, design, maternal and paternal education, paternal occupation, occupation, and parental country of birth, maternal household economy, maternal smoking status, maternal BMI, the number of siblings, and area-level SES.

higher zBMI in the single exposure model (which did not pass the multiple testing threshold), and associations between increased PM_{coarse}, land use mix and denser unhealthy food environment and several obesity outcomes in multiple exposure models. On the other hand, a combination of urban exposure of high levels of air pollution, road traffic, and road traffic noise was associated with increased zBMI and higher odds of overweight and obesity.

4.1. Urban environment and health

This study evaluated in three complementary steps the associations between multiple exposures and childhood obesity and weight-related behaviours. It allowed us to systematically report associations with all exposures, to adjust for multiple exposures, and to evaluate patters of multiple exposures. In fact, this is the first study to identify urban exposure patterns that may influence childhood obesity outcomes. We observed that an urban area with high levels of air pollution, road traffic, and road traffic noise may be associated with childhood obesity risk. In the single and multiple exposure we only observed few statistically significant associations, but the effect estimates for air pollution and noise were similar in magnitude and in direction to our results from the cluster analysis and to previous studies (Christensen et al., 2016; de Bont et al., 2019; Jerrett et al., 2010; Wang et al., 2020; Weyde et al., 2018). We found little evidence of associations between green space exposure variables and zBMI, whereas the literature shows largely inconclusive results (Luo et al., 2020). In single and multiple exposure models we may not have had enough power to detect single associations. Further, when we address each exposure in isolation we may actually capture other aspects of the urban environment; for example, it is not clear how much of the association of air pollution might be due to the actual air pollution concentration, or due to the effect of other highly correlated exposures. This may be overcome to some extent by the multiple exposure models (various exposures in one model), but in these models only a limited number of not too highly correlated exposures can be included due to colinearity problems. In our multiple exposure models the associations between land use mix and unhealthy food environment and overweight/obesity status became stronger and statistically significant. This indicates that these associations were influenced by confounding effects of the other urban exposures. In fact, not adjusting for other urban exposures may have obscured true effects in previous studies. By applying the cluster analysis, we are more likely to capture the urban environment as a whole, which may be another powerful way to examine multiple urban

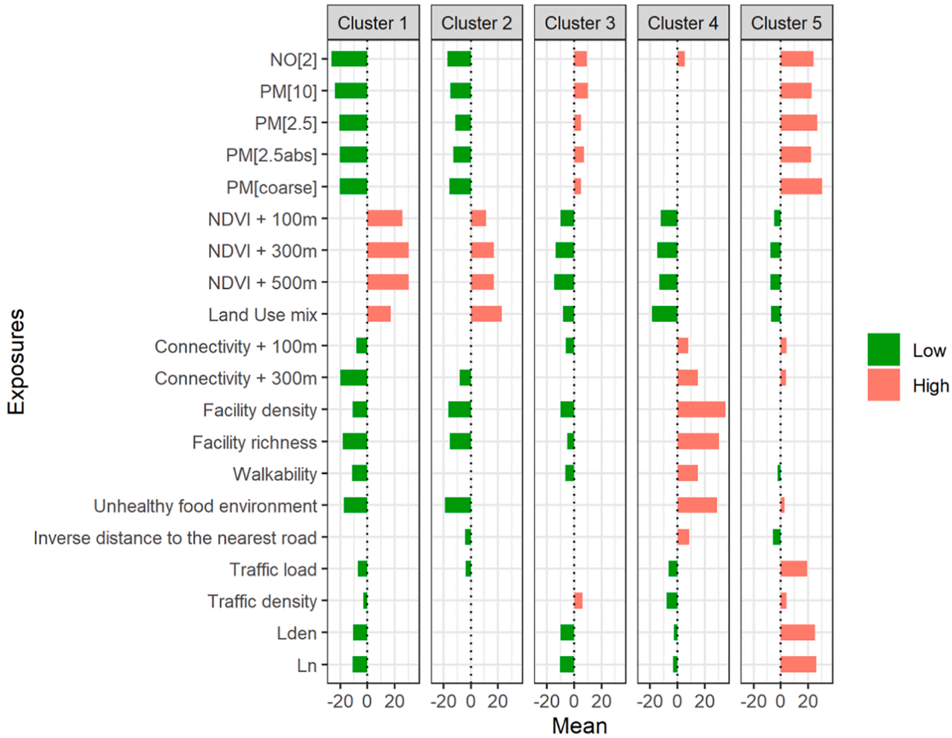

Fig. 3. Description of the clusters obtained from the hierarchical clustering on principal components analyses. The bars represent the deviation of the mean concentration of each urban exposure level in each cluster of the whole study population being 0. Red bars correspond to exposure levels above the mean in each specific cluster, whereas green bars correspond to exposure levels below the mean. All the exposures were previously conditioned on area-level socioeconomic status. Abbreviations: Lden, annual average of day, evening and night noise levels; Lden, annual average night noise levels; NDVI, Normalized Difference Vegetation Index; NO_2, nitrogen dioxide; NO_x, nitrogen oxides; $PM_{2.5}$, particulate matter with an aerodynamic diameter of less than 2.5 µm; PM_{10}, particulate matter with an aerodynamic diameter of less than 10 µm; PM_{coarse}, particulate matter with an aerodynamic diameter of between 2.5 than 10 µm; $PM_{2.5abs}$, absorbance of $PM_{2.5}$ filters. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

exposures with health. The fact that we only observe associations in cluster 5 and not in cluster 1 and 4 could be because the combination of exposures may neutralize the positive or negative effect of the individual exposures in the single and multiple exposure models. In addition, cluster 5, which has consistently higher levels of air pollution, road traffic and road traffic noise, and not many neutralizing exposures (average concentrations of green spaces and built environment factors), we actually observe an association with zBMI. A limitation of the cluster analysis is that it does not identify which of the exposures in each cluster are more likely to impact on childhood obesity. Overall, the results of the different models are important from a policy maker point of view, because long-term solutions to the childhood obesity epidemic may be achieved by modifying some specific aspects of the urban environment, and our results indicate that these should be focused on reducing levels of air pollution, road traffic and road traffic noise.

The mechanisms underlying the effects of the multiple urban exposures and childhood obesity are still poorly understood. Experimental studies in mice have found that air pollution may interfere with obesity pathogenesis at a molecular level inducing inflammation/oxidative stress, hormone disruption, and visceral adiposity (Sun et al., 2009; Xu et al., 2010). Noise could influence sleep deprivation and increase stress hormones, which are associated with physical development in childhood, increasing the risk of overweight in children (Münzel et al., 2017; Nielsen et al., 2011; Pervanidou and Chrousos, 2011). Increased access to unhealthy food environment may increase the consumption of fast-food consumption and increase caloric intake which is a known risk factor of childhood obesity (Townshend and Lake, 2016). Finally, contrary to what we expected, we observed that increased levels of land use mix were associated with increased levels of childhood obesity in the multiple exposure models. Our exposure assessment may not have captured well the different land uses in more densely populated areas, as these were categorized only as residential areas. It is only in the outskirts of the city that we found more diverse land uses, but these areas are more deprived and with less access to facilities, which may explain why we observed increased risk of childhood obesity.

4.2. *Weight-related behaviours*

It is well-known that weight-related behaviours have an important impact on the development of childhood obesity (Kumar and Kelly, 2017; Moreno et al., 2011; Woo Baidal et al., 2016). We observed that higher consumption to fast food restaurants and more screen time were associated with higher odds of overweight and obesity, whereas longer sleep duration during weekdays and better well-being were associated with lower odds of overweight and obesity. Childhood obesity is a direct consequence of a chronic imbalance between caloric intake and energy expenditure (Kipping et al., 2008; Trasande et al., 2010). Thus, increased consumption of fast food may contribute to increased caloric intake. Increased screen time may influence on a reduction of the energy expenditure creating a positive energy balance and increase weight gain (Mitchell and Byun, 2014). Short sleep duration has been associated with obesity in children (Hanlon et al., 2019). This association may be explained through multiple pathways including decrease of energy expenditure, increase appetite, and hormonal and neuroendocrine changes that would cause weight gain (Hanlon et al., 2019). Most of the pathways between poor mental health and obesity may go through increased appetite, and less time spent for physical activity (Liem et al., 2008).

We did not observe consistent associations between the urban exposures and weight-related behaviours. There are several possible explanations for this. The weight-related behaviours were self-reported by the parents, which could have introduced misclassification and recall bias. However, we did observe associations in the expected direction between the weight-related behaviours and overweight/obesity status, which makes it less likely that recall bias explains the lack of association. A more likely explanation is that the assessment of the behaviours in our study may not be context-specific in the urban environment where the behaviour occurs. The sole presence of green spaces and unhealthy food facilities does not necessarily imply increased physical activity or high fat caloric diet consumption, respectively. For example, green spaces and built environmental factors may increase physical activity and reduce levels of obesity through active commuting and recreational walking, and not through the leisure sport activities that were reported

Table 3
Associations between urban environment clusters and childhood obesity outcomes and weight-related behaviours.

Outcome	Cluster 1 N = 138 (6.2%)	Cluster 2 N = 610 (27.5%)	Cluster 4 N = 539 (24.6%)	Cluster 5 N = 237 (10.7%)
Anthropometric measures				
Age-sex zBMI score, beta (95% CI)	0.03 (−0.17; 0.24)	0.04 (−0.09; 0.16)	0.08 (−0.05; 0.21)	**0.17 (0.01; 0.34)**
Overweight/obesity status, OR (95% CI)	0.99 (0.67; 1.47)	1.02 (0.80; 1.30)	1.10 (0.86; 1.41)	1.36 (0.99; 1.85)
Waist circumference z-score, beta (95% CI)	0.06 (−0.11; 0.24)	0.03 (−0.07; 0.14)	0.06 (−0.05; 0.17)	0.12 (−0.02; 0.26)
Body fat (%) z-score, beta (95% CI)	0.06 (−0.12; 0.24)	0.02 (−0.09; 0.13)	0.09 (−0.02; 0.20)	0.11 (−0.03; 0.26)
Weight related behaviours:				
Fast food consumption in restaurants, OR (95% CI)	0.80 (0.43; 1.49)	0.90 (0.63; 1.28)	0.84 (0.57; 1.23)	1.02 (0.64; 1.60)
Sugar-sweetened beverage consumption, OR (95% CI)	1.10 (0.74; 1.63)	1.05 (0.83; 1.34)	1.20 (0.93; 1.54)	1.27 (0.93; 1.74)
Physical activity duration, beta (95% CI)	−0.82 (−2.48; 0.84)	−0.68 (−1.81; 0.44)	0.41 (−0.67; 1.49)	−0.21 (−1.67; 1.25)
Vigorous physical activity duration, beta (95% CI)	−1.21 (−2.57; 0.16)	−0.44 (−1.34; 0.46)	0.02 (−0.80; 0.85)	0.09 (−1.00; 1.17)
Screen time, beta (95% CI)	−1.37 (−2.99; 0.24)	1.00 (0.00; 2.00)	−0.02 (−1.04; 1.00)	−0.07 (−1.39; 1.24)
Sleep duration during weekdays, beta (95% CI)	0.01 (−0.11; 0.13)	−0.01 (−0.09; 0.06)	0.00 (−0.07; 0.07)	0.02 (−0.07; 0.12)
Well-being, OR (95% CI)	1.05 (0.72; 1.53)	0.87 (0.69; 1.10)	0.95 (0.75; 1.20)	0.78 (0.58; 1.06)

The beta estimates and OR for childhood obesity outcomes and weight related behaviours are compared with the reference category cluster 3 (N = 610 [27.6%]). Models were adjusted by study design, maternal and paternal education, paternal occupation, occupation, and parental country of birth, maternal household economy, maternal smoking status, maternal BMI, the number of siblings and area-level SES.

in our questionnaire. Future studies, incorporating more detailed questions on context-specific behaviours and real-time monitoring (e.g. of physical activity through accelerometers), would be needed to disentangle this. Furthermore, our main analysis focused on exposures at the residential address whereas other urban settings such as the school environment or the daily travel patterns are likely to have an impact on weight-related behaviours in children. However, our sensitivity analyses showed very similar associations with zBMI when using school instead of home exposures. Finally, for some combinations of exposures and weight-related behaviours there may not be much previous evidence of a direct associations. However, rather than omitting some of these combinations from our analyses, we chose to show all results as an exploratory, or "screening" analysis in the single exposure models, also because all these exposures were used to build the clusters.

4.3. Socioeconomic status

Socioeconomic status plays an important role in the associations between the urban environment and childhood obesity outcomes. In this study, children living in more deprived areas had higher rates of overweight and obesity, and were exposed to lower levels of air pollution, road traffic, road traffic noise and higher levels of green spaces. In Spain, lower SES areas have been consistently associated with increased levels of childhood obesity (de Bont et al., 2020a; Moreno et al., 2011), but the role of SES in urban environment studies is not clear and likely to vary by location (Hajat et al., 2015). In the US, people living in deprived areas have been reported to be exposed to higher levels of air pollution, whereas in European settings this is less consistent, showing that environmental inequality may not always be negative in direction (Hajat et al., 2015). A recent study, including 9 urban areas from 6 existing birth-cohort studies across Europe, including INMA Sabadell, reported that the association between SES and urban exposures varied between locations, with some showing more harmful exposures in lower and other in higher SES classes (both at individual and area level) (Robinson et al., 2018). In our study setting it seems that families with high SES prioritize living closer to the city centre of the urban area with higher levels of air pollution and less green spaces, rather than choosing to live in more environmentally "healthier" areas. Thus, the confounding effect by SES in the associations between the urban environment and weight-related outcomes was a special concern in our study. Therefore, we included many individual-level and area-level SES variables to minimize the potential impact of confounding by SES. Our sensitivity analysis showed that especially area SES had a large impact on effect estimates, and thus it is indeed important to adjust at both levels in these types of studies. However, we cannot fully rule out residual socioeconomic confounding, as SES is a complex construct and there may be components that are not captured in our variables. In the hierarchical clustering on principal components analysis we used SES standardised exposures. This avoided both the influence of the units of measurements (as recommended for principal component analysis (Gibson et al., 2019; Jollife and Cadima, 2016)) and the variance by SES, and minimized residual confounding by SES.

4.4. Strengths and limitations

This study has a number of strengths. First, we included multiple exposures in the urban environment, examined different childhood obesity outcomes (BMI, waist circumference and body fat percentage) and multiple behaviours (diet, physical activity, sedentary behaviour, sleep and well-being), allowing a comprehensive assessment of many weight-related outcomes. Second, we applied a statistical approach with three complementary steps that has several advantages in comparison with previous studies: (i) in the single exposure analyses we corrected the p-value for multiple testing which reduce false-positive results; (ii) in the multiple and all exposure models we accounted for confounding between urban exposures which are highly correlated; (iii) in the cluster analyses we evaluated urban exposure patterns that may have an impact on childhood obesity risk and weight-related behaviours.

As a limitation, our cross-sectional design may have limited causal inference between the urban exposures and childhood obesity and weight-related behaviours. This is especially a concern for the interpretation of the associations between weight-related behaviours and the odds of overweight and obesity, whereby the obesity status may have influenced in the change of the child behaviour (e.g. children with obesity may sleep less or have poorer mental health than normal weight children). We expect that reverse causality is less of a concern for the associations between urban exposures and obesity, as obesity status is unlikely to have influenced these exposures. However, as mentioned before, residential self-selection may have influenced our results as children with higher obesity levels (from lower SES areas) are more likely to live in less polluted and greener areas, which may have underestimated the association between urban exposures and childhood obesity. Studies with longitudinal follow-up are required to shed light on this. In addition, we were able to include many exposures related to the urban environment, but we could not include all and did not cover factors such as light at night, type and quality of green spaces, and blue spaces. Lastly, our study population was somewhat selective: schools that participated were more likely to be from less deprived areas than schools that did not (80% of the included school are located in the 1st and 2nd quintiles of deprivation, for the excluded schools this is 50%), and within participating school's children of lower socio-economic status may have been less likely to participate. This may have limited the generalisability of our results. However, as we observed similar childhood obesity levels in ECHOCAT, INMA and previous published studies in Catalonia (de Bont et al., 2020a), we consider that the sample is representative of the levels of childhood obesity in Catalonia, and further complex survey designs and sample weights were not applied.

5. Conclusion

This systematic study of many exposures in the urban environment suggests that an exposure pattern characterised by higher levels of ambient air pollution, road traffic and road traffic noise is associated with increased childhood obesity risk, and that PM_{coarse}, land use mix and food environment are separately associated with obesity risk. These findings require follow-up in longitudinal studies and different settings.

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CRediT authorship contribution statement

Jeroen de Bont: Conceptualization, Investigation, Methodology, Data curation, Formal analysis, Validation, Writing - original draft, Writing - review & editing, Project administration. **Sandra Márquez:** Methodology, Data curation, Validation, Formal analysis, Writing - review & editing. **Sílvia Fernández-Barrés:** Conceptualization, Methodology, Funding acquisition, Writing - review & editing. **Charline Warembourg:** Methodology, Validation, Formal analysis, Writing - review & editing. **Sarah Koch:** Conceptualization, Methodology, Writing - review & editing. **Cecilia Persavento:** Investigation, Writing - review & editing. **Silvia Fochs:** Investigation, Writing - review & editing. **Núria Pey:** Investigation, Writing - review & editing. **Montserrat de Castro:** Investigation, Resources, Writing - review & editing. **Serena Fossati:** Methodology, Investigation, Writing - review & editing. **Mark Nieuwenhuijsen:** . **Xavier Basagaña:** . **Maribel Casas:** Conceptualization, Methodology, Funding acquisition, Writing - review & editing. **Talita Duarte-Salles:** Conceptualization, Methodology, Supervision, Project administration, Funding acquisition, Resources, Writing - review & editing. **Martine Vrijheid:** Conceptualization, Methodology, Supervision, Project administration, Funding acquisition, Resources, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

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

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2021.106700.

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