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Urban environment and health behaviours in children from six European countries

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ABSTRACT

Background: Urban environmental design is increasingly considered influential for health and wellbeing, but evidence is mostly based on adults and single exposure studies. We evaluated the association between a wide range of urban environment characteristics and health behaviours in childhood.
Methods: We estimated exposure to 32 urban environment characteristics (related to the built environment, traffic, and natural spaces) for home and school addresses of 1,581 children aged 6–11 years from six European cohorts. We collected information on health behaviours including total amount of overall moderate-to-vigorous physical activity, physical activity outside school hours, active transport, sedentary behaviours and sleep duration, and developed patterns of behaviours with principal component analysis. We used an exposure-wide association study to screen all exposure-outcome associations, and the deletion-substitution-addition algorithm to build a final multi-exposure model.
Results: In multi-exposure models, green spaces (Normalized Difference Vegetation Index, NDVI) were positively associated with active transport, and inversely associated with sedentary time (22.71 min/day less (95 %CI −39.90, −5.51) per interquartile range increase in NDVI). Residence in densely built areas was associated with

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more physical activity and less sedentary time, and densely populated areas with less physical activity outside school hours and more sedentary time. Presence of a major road was associated with lower sleep duration (-4.80 min/day (95 %CI −9.11, −0.48); compared with no major road). Results for the behavioural patterns were similar.

Conclusions: This multicohort study suggests that areas with more vegetation, more building density, less population density and without major roads are associated with improved health behaviours in childhood.

1. Introduction

Risk of non-communicable diseases (NCDs) is associated with insufficient physical activity, increased sedentary time and inadequate sleep (Chaput et al., 2018; GBD 2016 Risk Factors, 2018; Stiglic and Viner, 2019; World Health Organization, 2020). The Word Health Organization (WHO) recommendation is to achieve at least 60 min a day of moderate-to-vigorous physicial activity, but<45% of children worldwide meet this recommendation (Roman-Viñas et al., 2016). Children are becoming more sedentary and 20% to 67.7% of European children spend two or more hours per day of screen time depending on the country (Whiting et al., 2021).

Vulnerability to NCDs has been attributed to adverse individual choices rather than recognising the importance of wider, complex systems (Knai et al., 2018). Poorer areas with polluted roads and low walkability, poor quality green spaces to play and exercise and unsafe neighbourhoods with low quality physical infrastructure are wider determinants that create a clustering of environmental risks that may lead to unhealthy behaviours and subsequent risk of NCDs and widening of health inequalities. Thus, there is an increasing interest in studying the contribution of the urban environment to unhealthy behaviours among children, and whether a change in the urban design may be beneficial for promoting a healthier lifestyle (Masoumi, 2017). Most of the literature is based on observational studies and focuses on overall physical activity and walking (Townshend and Lake, 2017). However, the evidence available is mostly focused on adults, and for children it is weak and inconsistent for some indicators (Casey et al., 2014; Ding et al., 2011; Masoumi, 2017; Timperio et al., 2015). These discrepancies could be partly explained by the indicators used; some of the studies used perceived indicators and others objectively measured indicators. Furthermore, studies have mainly assessed a single urban environment indicator with respect to a single health behaviour, while only a few took into account multiple urban indicators (Buck et al., 2019; Casey et al., 2014; de Bont et al., 2021; McGrath et al., 2015; Townshend and Lake, 2017). Exposures in the urban environment are known to be highly correlated (Robinson et al., 2018), so addressing each exposure in isolation is unlikely to adequately account for correlated co-exposures. Also, the identification of combinations of exposures that are more likely to affect health or health behaviours, may help policymakers and urban planners to tackle multiple factors to make cities healthier and more liveable (Nieuwenhuijsen et al., 2017). To our knowledge, no study has investigated the association between multiple urban indicators and patterns of health behaviours in childhood.

Given the potential for the urban environment to influence child health behaviours, our aim was to evaluate the association between several objectively measured urban environment indicators from different domains, namely the built environment, traffic and natural spaces, and several health behaviours and their patterns, in children of primary school age from six European cohorts.

2. Methods

2.1. Study population

This study is based on the Human Early-Life Exposome (HELIX) study (Maitre et al., 2018), a collaborative project across six longitudinal population-based European birth cohorts: Born in Bradford (BiB; UK), Étude des Déterminants pré et postnatals précoces du développement et de la santé de l'Enfant (EDEN; France), INfancia y Medio Ambiente (INMA; Spain), Kaunas cohort (KANC; Lithuania), Norwegian Mother, Father and Child Cohort Study (MoBa; Norway), and the RHEA Mother Child Cohort study in Crete (Greece).

We used data from the HELIX subcohort, consisting of an additional follow-up visit for the mother–child pairs between 2013 and 2016, when children were 6–11 years of age. Details on the selection of the subcohort population and baseline characteristics of the entire cohorts and subcohorts are described by Maitre et al. (2018). The follow-up visit consisted of a clinical examination of the children, biosample collection, and questionnaires with their parents, following a common protocol across the six countries. Standardized data collection was performed by trained staff. Approval was obtained from the ethics committees in every site. All participating women provided informed written consent.

2.2. Urban environment

We obtained the residential and school address of each child during the HELIX follow-up visit, and these were geocoded to derive urban environment indicators by using the following software: the PostgreSQL (copyright © 1996–2017 The PostgreSQL Global Development Group), PostGIS (Creative Commons Attribution-Share Alike 3.0 License https://postgis.net) and QGIS (QGIS Development Team, 2016. QGIS Geographic Information System). The detailed exposure assessment is described elsewhere (Nieuwenhuijsen et al., 2019; Robinson et al., 2018; Tamayo-Uria et al., 2019). The urban environment exposures derived were surrounding natural spaces, built environment, and traffic; their assessment is described in detail in **Annex** and their sources of data are shown in **Table A.1.** The urban areas from the six cohorts were: BiB based in Bradford (United Kingdom), EDEN in Poitiers (France), INMA in Sabadell (Spain), KANC in Kaunas (Lithuania), MoBa in Oslo (Norway), and RHEA in Heraklion (Greece).

Surrounding natural space indicators included the Normalized Difference Vegetation Index (NDVI), distance to major green space, and presence of major green and blue spaces. The Normalized Difference Vegetation Index (NDVI) is an indicator of greenness (with higher numbers indicating more greenness) (Nieuwenhuijsen et al., 2014; Rhew et al., 2011). NDVI were derived from satellite images (Landsat 4–5 TM, Landsat 7 ETM+, and Landsat 8 OLI/TIRS) with 30 m × 30 m resolution. Best images for one date of the follow-up period were selected according to the following criteria: a) <10% are covered by clouds; b) Standard Terrain Correction (Level 1 T); and c) greenest period of the year (spring in RHEA and INMA, and summer in KANC, MOBA, BiB and EDEN). We used the 100-m buffer for NDVI. As proxies of access to natural spaces, we calculated the distance from home and school to the nearest major green space (parks or countryside) and the presence of an area (greater than 5,000 m^2) green or blue (bodies of water) as dichotomous variable (present or not within a 300-m buffer (approximately within 15 min walk for children)) from Europe-wide or local topographical maps (Smargiassi et al., 2009; Urban atlas).

Built environment factors were calculated from topological maps obtained from local authorities or from Europe-wide sources. Buffers of 100 and 300 m were used, but in this study only the 300-m buffer estimates were included due to the high correlations between variables. We calculated building density (within the 300-m buffer) by dividing the area of building cover (km^2) by the area of buffer (km^2). We calculated population density as the number of inhabitants (per km^2) surrounding the home and the school area, and the street connectivity as the number of intersections by the area (km^2) inside the 300-m buffer. We calculated a facility richness index based on the number of different facility types (e.g. community services, schools, financial institutions, entertainment, parks, and recreation) divided by the maximum potential number of facility types specified in a buffer of 300 m (score range from 0 to 1) (Smargiassi et al., 2009; Urban atlas). A facility density index was calculated as the number of facilities divided by the area of the buffer (number of facilities/km^2). A higher value indicates a greater availability of different facility types. Mixed land use was calculated by the Shannon's Evenness Index as the proportional abundance of each type of land used within the 300-m buffer (score range from zero to one) (Shannon, 2001). We multiplied each proportion of land use type by its logarithm and divided the sum of all land use type products by the logarithm of the total possible land use types. Access to public transport was calculated as the number of bus stops and meters of bus lines inside 300-m buffer based on maps from local authorities and OpenStreetMap® ("OpenStreetMap,"). We created an indicator of walkability, based on previously developed indicators (Duncan et al., 2011; Frank et al., 2006), calculated as the mean of the sum of the deciles of population density, street connectivity, facility richness, and land use within 300-m buffers (score range from zero to one).

Traffic density indicators were calculated from road networks maps following the protocol of the ESCAPE project and using a 100-m buffer (Beelen et al., 2013; Eeftens et al., 2012). We included in this analysis the following traffic indicators: traffic density on the nearest road, total traffic load on all roads, presence of a major road, and inverse distance to the nearest major road.

2.3. Outcome assessment

Information on health behaviours was obtained through standardized questionnaires at age 6–11 years, reported by the parents. It included moderate-to-vigorous physical activity, physical activity outside the school hours, sleep duration, sededentary activies and active transport from home to school, all reported as minutes per day.

2.3.1. Physical activity

The questionnaires collected information on frequency, intensity, and duration of time spent regularly performing physical activity during school hours, outside the school hours at weekdays and during weekends. We calculated physical activity outside the school hours (in min/day) based on the time spent playing outside the school hours and at weekends (including light, moderate and vigorous activity). We obtained total moderate-to-vigorous physical activity (min/day) as the amount of time children spent doing physical activities (during school hours, outside school, and at weekends) with intensity above three metabolic equivalents (METs) (Ridley et al., 2008).

2.3.2. Sleep duration

In the questionnaires, the parents reported the earliest and latest bedtimes and wake-up times during weekdays and weekends, reflecting usual sleep patterns. Based on the average bedtime and wake-up time, we calculated the average nighttime sleep duration (weighted average of weekdays and weekend sleep duration), and it is expressed as min per day.

2.3.3. Sedentary behaviours

We asked parents to report their children's time spent watching television, playing computer or video games and other sedentary activities during weekdays and weekends. We considered sedentary activities as "any waking behaviour characterized by an energy expenditure < 1.5 metabolic equivalent tasks (METs) while in a sitting or reclining posture" by the Sedentary Behaviour Research Network. We calculated the average time spent daily (in minutes) watching television, playing computer or video games and other sedentary activities (eg. reading, puzzles), and the sum of these activities as total sedentary time (Sedentary Behaviour Research Network, 2012).

2.3.4. Active transport from home to school

We also calculated daily time performing active commuting from home to school based on the data obtained through the QGIS, which is a free and open source Geographic Information System (Version 1.8.0 – http://www.qgis.org/en/site/). The participants were asked to draw the common route they performed from home to school and indicate the mode of transport. Based on this information we calculated daily active transportation based on the time spent walking and cycling to school.

2.3.5. Health behaviours patterns

We performed a principal component analysis (PCA) of the health behaviour outcomes including physical activity outside the school hours, sleep duration, television time, time playing computer games, time performing other sedentary activities, and active transport. We used the "FactoMineR" command in the base R package. Outcomes were centred by the mean and unit variances scaled. After varimax rotation three principal components were retained for the analysis based on eigenvalues (greater than1) and the scree test, and explained 56% of cumulative variance. Each participant received a score for each of the principal components. These principal components were used in the analysis as outcome patterns, in addition to the individual outcomes.

2.4. Covariates

We collected information on key covariates during pregnancy and in the subcohort follow-up assessment. Covariates included are maternal educational status (defined as the highest level of education reporter by the mother, and it was categorized according to the International Standard Classification of Education (ISCED) as: low, middle, high education) (Eurostat, 2016), family affluence score (as a measure of the family's economic capital. We calculated based on the responses to four questions asked to the participants: a) Does your family own a car, van or truck?; b) Do you have your own bedroom for yourself?; c) During the past 12 months, how many times did you travel away on holiday with your family?; d) How many computers does your family own?) (Boyce et al., 2006; Liu et al., 2012), area level socio-economic status (SES) (it was defined based on area level measures of deprivation or SES indicators for the home address of the participant in tertiles, 1st tertile less deprivated, 3rd tertile most deprivated, based on the entire cohort distribution (Maitre et al., 2018). For the BiB study the UK Index of Multiple Deprivation was used (Department for Comminities and Local Governments, 2015), for EDEN the French European deprivation index score (Pornet et al., 2012), for INMA cohort we used the Spanish Urban vulnerability index at census level (Department of Architecture, 2001). For MoBa, we used tertiles of average personal income of the area (Statistics, 2013). For KANC and RHEA the proportion with high education of the voting district and aggregated lower census area was used, respectively (Hellenic Statistical Authority, 2001; Smith et al., 2017). Other variables collected are child age (years) and child sex (male/female).

2.5. Statistical analysis

First, we calculated the Pearson's correlations between continuous exposures and we removed those indicators that had a high correlation (above 0.80) with other spatial indicators. We focused on a reduced urban environment dataset of 32 variables and we explored the distribution of these variables before imputation, and we transformed the variables that showed skewed distributions or we categorized them if normality could not be achieved for the imputation process. Then, the distribution of all transformed variables was examined to ensure that transformation did not lead to extreme or influential observations.

Missing rates in the exposures ranged from 0.4% in Facility density and Population density (at home) to 44.3% in Accessibility (bus lines) at school. The mean percentage of missing values among the exposures was 10.9%. We used multiple imputation to deal with missing values in exposures and covariates (**Table A.2**) by using the chained equations method, as described in detail elsewhere (Tamayo-Uria et al., 2019; White et al., 2011). In total, 20 imputed datasets were generated using the MICE package in R. This approach has been considered superior to excluding the entire cohort or the exposure (Held et al., 2016; Jolani et al., 2015).

We standardised all the exposures by the interquartile range (IQR) and first used an exposome-wide association study (ExWAS) approach to screen associations for all the exposures independently. This approach consisted of a exposure-by-exposure estimation of the exposure-outcome association by independent linear regression models adjusting for potential confounders. To correct for multiple hypothesis testing, each p value was compared with a threshold, defined as 0.05 divided by the effective number of tests (Li et al., 2012), the corrected p value was 0.003 in the analysis with home and school exposures (i.e. moderate-to-vigorous physical activity, physical activity outside school hours, and active transport), and 0.005 in the analysis with only home exposures (i.e. sleep duration, sedentary behaviours and patterns (PCAs)). We considered only home exposures for these outcomes, because these activities are usually performed at home. ExWAS models were fitted separately in each imputed dataset, and results were combined using the usual multiple imputation rules to account for imputation uncertainty.

We then used the deletion/substitution/addition (DSA) algorithm method to select a reduced number of exposures and build a final multi-exposure model (Sinisi and Van Der Laan, 2004). This method showed better model selection efficiency (particularly a lower false positive rate), in comparison with other linear regression-based methods in exposome studies, including a running multiple exposure model based on ExWAS results, as described by Agier et al. (Agier et al., 2016). The DSA algorithm method is an iterative process based on deletion of variables from those selected in a model, substitution of the selected variables by unselected ones or addition of new variables, with the purpose of selecting a final model by minimizing the value of the root mean squared error of predictions using 5-fold cross-validated data. We fitted the DSA 50 times on the data using different seeds to stabilize the cross-validation results. We retained for our final multiexposure regression model the exposures selected in at least 10% of the DSA runs. This cut-off was arbitrary and selected a priori to reduce false positive findings. We checked for potential multicollinearity among the selected exposures in the final multiexposure model, based on the correlation between the variables, and the variance inflation factor (VIF). In our analysis, multicollinearity occurred only for road traffic load and was excluded from the final multiexposure models of sleep duration. For the rest of the variables there was little evidence of collinearity in the multiple exposure models in that VIFs were all below < 4 (being these values no alarmant in the sense that conserved the stability of the estimated coefficients and the variance). We applied DSA (not allowing for polynomials or interaction terms) to the 20 imputed data sets by stacking them one after the other and using weights to correct the standard errors. Once the variables were selected, a final model was fitted including only the selected variables and using the usual multiple imputation procedures to account for imputation uncertainty in the final confidence intervals. This method has been shown to be a reasonable approach to conduct variable selection with multiply imputed data (Wood et al., 2008).

All single and multiexposure models were adjusted for cohort, child age (years), child sex (male, female), maternal education (low, middle, high), family affluence score (as a measure of the family's economic capital) and area level SES (deprivation index; in tertiles), based on the literature.

2.5.1. Sensitivity analyses

We performed the following sensitivity analyses: a) We repeated the multiexposure model restricted to complete cases; b) We ran the final multiexposure model by cohort and evaluated between-cohort heterogeneity of associations (using the I^2 statistic) (Higgins and Thompson, 2002); c) We stratified the multiexposure model by sex to obtain sex-specific estimates and we included an interaction term in the model to test for potential effect modification by sex; d) We stratified the multi-exposure model by maternal education (low/medium and high) and by area level SES to examine the robustness of results across socio-economic classes, and we included an interaction term in the model to test for a potential interaction; e) We explored the role of the distance from home to school (calculated from the routes drawn in the QGIS) in analyses of the active transportation outcome, by adding this variable in a complementary model and stratifying by distance below 800 m and above 800 m to obtain specific estimates (Timperio et al., 2006). We tested for potential interactions.

All analyses were run under R version 3.6.1 (R Foundation, Vienna, Austria).

3. Results

3.1. Descriptives

Our study included 1581 children from six European cohorts (Table 1). Children were on average (SD) 8.19 (1.5) years old (cohort variations shown in **Table A.3**). Children performed 53 (39.7) minutes of physical activity outside the school hours, 614.97 (41.3) min of sleep, 224 (92.2) minutes of sedentary activities and 6.90 (8.4) minutes of active transport per day. 36.4% met the WHO recommendations of at least 60 min per day of moderate-to-vigorous physical activity. 58.6% had more than 2 h per day of screen time. There was variation in health behaviours across cohorts (**Table A.4**). Spanish children (INMA) had the greatest duration of physical activity outside the school (65 (SD 37.2) min/day) and children from the French cohort (EDEN) the least (28 (22.6) min/day). Children from BiB cohort were the ones with the greatest TV watching time (115.7 (58.67) min/day) and children from MoBa the least (92.4 (47.94) min/day). Active transport ranged from 13 (9.9) min/day in MoBa to 1.9 (3.9) min/day in RHEA.

The urban exposures and their correlations are shown in Table 2 **and Figure A.1**, with differences across cohorts (**Table A.5**). MoBa and EDEN had the highest mean NDVI. The southern cohorts (INMA and RHEA) had more surrounding traffic load close to home compared to the other cohorts. INMA had the highest population and building density (mean 16,000 inhabitants/m^2 and 350,000 m^2 built/km^2). The mean walkability index was similar across cohorts, with INMA having the highest mean score (0.41 (SD 0.17)) and EDEN the lowest (0.28 (0.08)).

3.2. Exposome-wide association study and deletion/substitution/addition (DSA) algorithm

Seven environmental exposures were associated with moderate-to-vigorous physical activity in the ExWAS analysis ($p < 0.05$), but only the association between home NDVI passed the multiple testing corrected p-value of 0.003 (8.72 min/day, 95 %CI 3.22, 14.21 per IQR increase); Fig. 1**A; Table A.6).** This association was attenuated in the final multi-exposure model (β 7.00 min/day, 95 %CI −0.38, 14.38) (Table 3). In this multi-exposure model, building density was associated with overall moderate-to-vigorous physical activity (β 6.39 min/day, 95 %CI 1.80, 10.98).

For physical activity outside the school hours, seven urban exposures showed associations in the ExWAS (Fig. 1**B; Table A.7**). In the multi-exposure model, population density was negatively associated with the time performing physical activity outside the school hours (β −3.80, 95 %CI −6.97, −0.64), and building density with more physicial activity (β 6.59, 95 %CI 2.33, 10.86; Table 3).

Table 1
Description of the study population (N = 1,581).

	N (%)	Mean (SD)
Cohort		
BiB (UK)	229 (14.5)	
EDEN (France)	195 (12.3)	
INMA (Spain)	492 (31.1)	
KANC (Lithuania)	190 (12.0)	
MoBa (Norway)	288 (18.2)	
RHEA (Greece)	187 (11.8)	
Child sex		
Female (%)	728 (46.1)	
Male (%)	853 (53.9)	
Child age, years ± SD		8.19 (1.5)
Family Affluence Score, score ± SD		5.33 (1.4)
Area Level SES		
1st Tertile (%)	601 (40.6)	
2nd Tertile (%)	568 (38.3)	
3rd Tertile (%)	312 (21.1)	
Maternal education level		
Low (primary school) (%)	233 (15.7)	
Middle (secondary school) (%)	514 (34.7)	
High (University or higher) (%)	733 (49.5)	
Moderate-to-vigorous physical activity (min/day)		49.5 (40.4)
Moderate-to-vigorous physical activity ≥ 60 (min/day) (%)	576 (36.4)	
Physical activity outside the school hours (min/day)		52.7 (39.7)
Sleep duration (min/day)		614.97 (41.3)
Sedentary time (min/day)		224.3 (92.2)
Television time (min/day)		103.7 (53.9)
Computer games (min/day)		42.1 (41.5)
Other sedentary activities (min/day)		78.5 (56.9)
Active transport (min/day)		6.9 (8.4)

Abbreviations: BiB, Born in Bradford study cohort; EDEN, Étude des Déterminants pré et postnatals précoces du développement et de la santé de l'Enfant; INMA, INfancia y Medio Ambiente study cohort; KANC, Kaunas study cohort; MoBa, the Norwegian Mother, father and Child Cohort; RHEA, RHEA Study Mother and Child Cohort; SD, Standard deviation; SES, Socio-economic status.

In the ExWAS analysis (Fig. 1**C; Table A.8**), nine exposures were associated with active transport, three passing the multiple correction threshold: greater facility richness and density were associated with more active transport, and greater land use diversity with a decrease of active transport. In the multi-exposure model, greater distance to the nearest green space, land use diversity within home area, and street connectivity around the school were associated with less active transport, while higher facility density around the home area was associated with more active transport (Table 3). The sizes of these associations were all around 1 min/day.

Home proximity to a major road was the only variable associated with sleep duration, with a decrease of −4.80 (95 %CI −9.11,-0.48) min/day, both in the ExWAS and in the multi-exposure model (Fig. 1**D; Table A.9;** Table 3).

Some urban indicators were related to sedentary behaviours, as shown in Fig. 1**E** and **Table A.10**. Higher vegetation (home NDVI) was associated with a decrease of −20.40 min/day (95 %CI –32.98, −7.82)

Table 2
Exposure levels at home and school.

Exposure	All cohorts
Home	
NDVI-100 m, mean ± SD	0.42 ± 0.17
Green distance, mean ± SD	190 ± 180
Green spaces Yes (vs. No), n (%)	1153 (78.38)
Blue spaces Yes (vs. No), n (%)	107 (7.27)
Road traffic load-100 m, mean ± SD	1600000 ± 3400000
Major road-100 m (vs. no major road), n (%)	326 (36.30)
Traffic density on nearest road, mean ± SD	10000 ± 15000
Inverse distance to nearest road, mean ± SD	0.14 ± 2.50
Population density, Inhabitants/ km^2 ± SD	8200 ± 9900
Building density-300 m, mean m^2 built/km^2 ± SD	200000 ± 150000
Connectivity-300 m, mean ± SD	160 ± 100
Accessibility (bus lines-300 m), mean ± SD	691 (78.26)
Accessibility (bus stops-300 m), mean ± SD	14.00 ± 13.00
Facility richness-300 m, mean ± SD	0.07 ± 0.07
Facility density-300 m, mean ± SD	30.00 ± 44.00
Land use-300 m, mean ± SD	0.40 ± 0.13
Walkability index, mean ± SD	0.34 ± 0.10
School	
NDVI-100 m, mean ± SD	0.39 ± 0.14
Green distance, mean ± SD	200 ± 200
Green spaces Yes (vs. No), n (%)	1122 (76.69)
Blue spaces Yes (vs. No), n (%)	105 (7.18)
Major road-100 m (vs. no major road), n (%)	279 (31.00)
Inverse distance to nearest road, mean ± SD	0.03 ± 0.10
Population density, Inhabitants/ km^2 ± SD	7100 ± 7500
Building density-300 m, mean m^2 built/km^2 ± SD	220000 ± 150000
Connectivity-300 m, mean ± SD	160 ± 95
Accessibility (bus lines-300 m), mean ± SD	706 (80.23)
Accessibility (bus stops-300 m), mean ± SD	14.00 ± 12.00
Facility richness-300 m, mean ± SD	0.09 ± 0.08
Facility density-300 m, mean ± SD	47.00 ± 78.00
Land use-300 m, mean ± SD	0.42 ± 0.14
Walkability index, mean ± SD	0.35 ± 0.09

Abbreviations: NDVI, Normalized Difference Vegetation Index; SD, Standard deviation.

overall sedentary time in the ExWAS analysis, similar decreases was observed in the sedentary sub-activities (TV viewing and computer games (data not shown)). In multi-exposure models, higher vegetation was associated with lower sedentary time (Table 3). Population density was associated with higher sedentary time in the ExWAS, but this association was attenuated in the multi-exposure model. Building density was associated with a decrease of sedentary time in the multi-exposure models (β −10.55 min/day, 95 %CI −20.27, −0.82). These patterns of associations were similar to the results for TV viewing (data not shown).

To study the health behaviours in combination, we performed PCA and the loadings are shown in Fig. 2. PC1 (26.2% of variance) described higher moderate-to-vigorous physical activity and higher physical activity outside the school hours. This pattern was associated with 5 exposures in the ExWAS, but none passed the multi-testing correction threshold ($p < 0.005$) (Fig. 2**A** and **Table A.11**). Some of these associations remained similar in the multi-exposure model (e.g. population density and street connectivity), however other associations were attenuated, like NDVI. Building density was associated with an increase in PC1 score (β 0.16, 95 %CI 0.05, 0.28) in the multi-exposure model (Table 4). PC2 (19.7 % of variance) described more screen time and less sleep, and was associated with two exposures in the ExWAS: population density (β 0.09, 95 %CI 0.02, 0.15) and NDVI (β −0.17, 95 %CI −0.31, −0.03) (Fig. 2**D, Table A.11**). The estimates for these associations were weaker in the multi-exposure model and no longer statistically significant. PC3 (15.3 % of variance) described more time of active transport and sleep duration, and less other sedentary behaviours. In the ExWAS, accessibility to public transport, facility richness and density were associated with an increase in PC3 score, and land use with a decrease (Fig. 2**F, Table A.11**). In the multi-exposure models, distance from home to green spaces and walkability index decreased PC3 score, and facility density was associated with higher PC3 score.

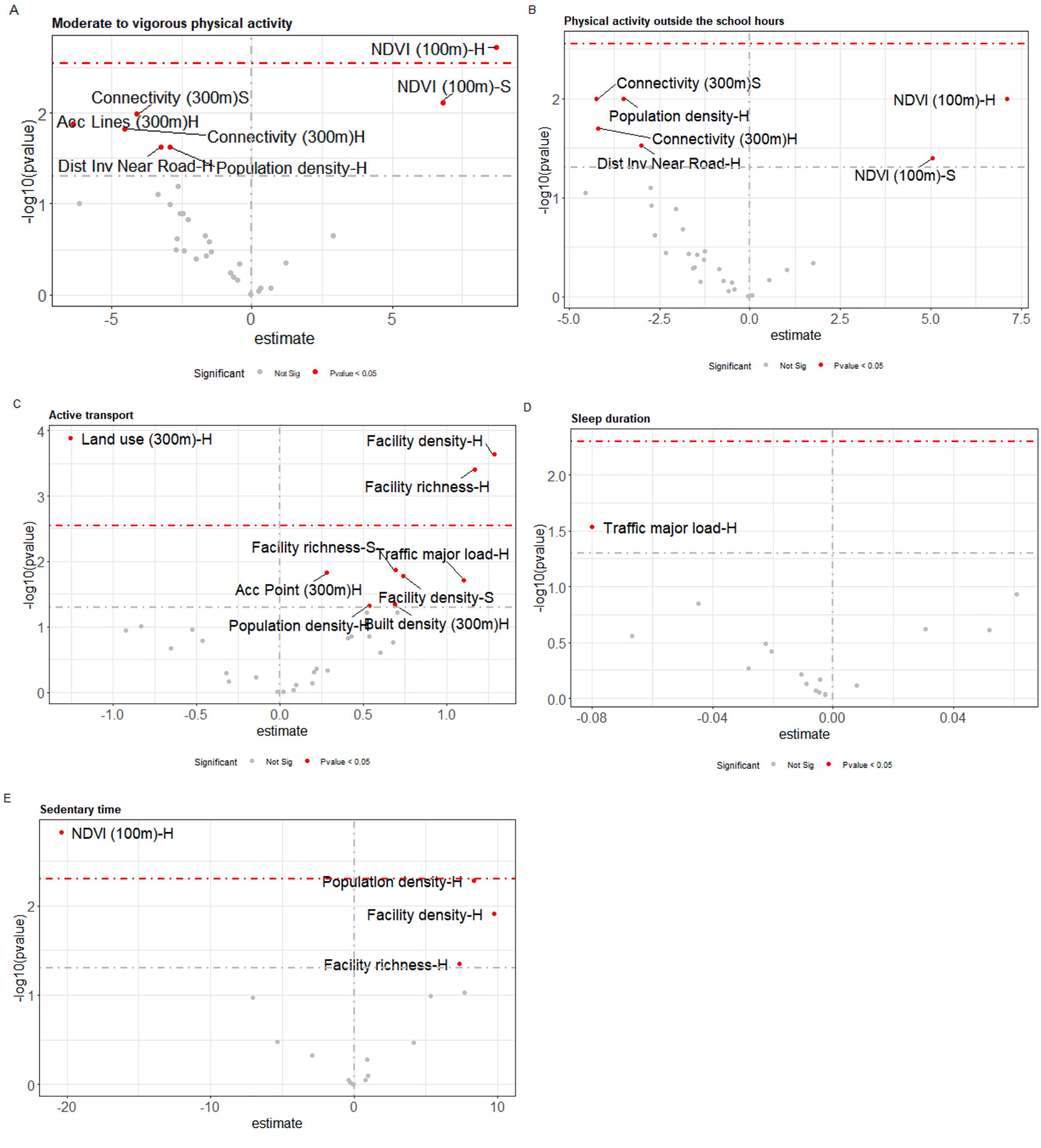

Fig. 1. Association between the urban environment exposures and behavioural patterns in childhood in single-exposure ExWAS model. Volcano plot showing significance (p-value) against beta coefficient. Black dashed horizontal line at p-values of 0.05; red solid horizontal line at TEF of 0.003 [(A), (B), (C)] and 0.005 [(D), (E)]. Beta estimates for all exposures are shown in **Tables A.6–10**. Models adjusted for cohort, child age, child sex, maternal education, family affluence score and area level SES. Note: Beta coefficient for change in outcomes compared with reference category for the categorical variables. For continuous variables, beta estimates are calculated per interquartile range increase in exposure. Abbreviations: Acc Lines, Accessibility (bus lines-300 m); Acc Point, Accessibility (bus stops-300 m); Dist Inv Near Road, Inverse distance to nearest road; Green dist, Green distance; H, Home; NDVI, Normalized Difference Vegetation Index (100 m); S, School; TEF, threshold for effective number of test (i.e., p-value correction for multiple testing). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Analysis of the association between home and school exposures, and single lifestyle behaviours in childhood (N = 1,581). Only exposures selected in at least one DSA are shown.

	Moderate-to- vigorous physical activity (min/day)	Physical activity outside the school hours (min/day)	Active transport (min/day)	Sleep duration (min/day)	Sedentary time (min/day)
Exposure (IQR or category)[a]	Estimate (95% CI)	Estimate (95% CI)	Estimate (95% CI)	Estimate (95% CI)	Estimate (95% CI)
Home					
NDVI-100 m (0.31)	7.00 (-0.38, 14.38)	5.70 (-1.43, 12.83)	ns	ns	−22.71 (-39.90, −5.51)
Green distance (213.25 m)	ns	ns	−0.94 (-1.67, −0.22)	ns	ns
Road traffic load-100 m (1,974,930 vehicles/day m)	ns	ns	ns	*	−5.58 (-14.33, 3.17)
Major roads-100 m (*vs.* no major road)	ns	ns	0.69 (-0.26, 1.64)	−4.80 (-9.11, −0.48)	ns
Traffic density on nearest road (11,033.1 vehicles/day)	−2.99 (-6.78, 0.81)	ns	ns	ns	−6.64 (-15.57, 2.30)
Inverse distance to nearest road (0.04 m^{-1})	−2.04 (-4.98, 0.91)	−1.87 (-4.75, 1.02)	ns	ns	ns
Population density (7,550.89 people/ km^2)	−1.37 (-4.40, 1.65)	−3.80 (-6.97, −0.64)	ns	ns	5.53 (-1.60, 12.67)
Building density-300 m (174,887.9 m^2 built/km^2)	6.39 (1.80, 10.98)	6.59 (2.33, 10.86)	ns	ns	−10.55 (-20.27, −0.82)
Connectivity-300 m (142.38 number of intersections/km^2)	−2.30 (-6.64, 2.03)	−4.25 (-8.66, 0.15)	0.63 (-0.25, 1.50)	ns	ns
Accessibility (bus lines-300 m) 1 or more (*vs.* none)	−4.95 (-10.48, 0.58)	−3.83 (-9.69, 2.03)	ns	ns	ns
Accessibility (bus stops-300 m) (17.8 bus stops/ km^2)	ns	ns	0.17 (-0.08, 0.42)	ns	ns
Facility density-300 m (38.90 facilities/km^2)	ns	ns	1.25 (0.41, 2.09)	ns	5.96 (-4.78, 16.70)
Land use-300 m (0.19)	2.44 (-0.83, 5.70)	ns	-1.35 (-2.05, -0.65)	ns	ns
Walkability index (0.15)	ns	4.44 (-0.41, 9.28)	ns	ns	ns
School					
NDVI-100 m (0.24)	5.14 (-0.84, 11.11)	ns	ns	–	–
Green distance (223.46 m)	ns	ns	0.54 (-0.10, 1.18)	–	–
Green spaces Yes (*vs.* No)	−5.06 (-10.11, 0.00)	ns	ns	–	–
Blue spaces Yes (*vs.* No)	−6.27 (-13.55, 1.01)	ns	ns	–	–
Inverse distance to nearest road (0.02 m^{-1})	ns	ns	−0.44 (-0.98, 0.09)	–	–
Connectivity-300 m (117.47 number of intersections/km^2)	−3.01 (-6.80, 0.78)	−2.94 (-6.23, 0.35)	−1.16 (-1.94, −0.37)	–	–
Accessibility (bus stops-300 m) (17.8 bus stops/ km^2)	2.83 (-1.94, 7.61)	ns	0.77 (-0.27, 1.82)	–	–

[a] Reference category as indicated inside brackets for the categorical variables. For continuous variables, estimates are calculated per interquartile range increase in exposure, as indicated inside brackets; IQRs calculated on the first imputed dataset after back transforming the variables. Models adjusted for cohort, child age, child sex, maternal education, family affluence score and area level SES. Beta estimates for all exposure variables selected in 10% or more of DSA runs and frequency of selection are shown in Tables S6-S10. Abbreviations: DSA, Deletion/substitution/addition algorithm; NDVI, Normalized Difference Vegetation Index; ns, not selected in the DSA model. *This variable was selected by the DSA but not included in the final multi-exposure model for the stability of the model.

3.3. Sensitivity analyses

Results from our sensitivity analysis using complete case analysis were generally similar to the imputed analysis, except for greenness and moderate-to-vigorous physical activity and physical activity outside the school hours (**Table A.12** and **Table A.13**). The observed associations were consistent across cohorts (**Figure A.2**), with little evidence of heterogeneity (I^2 between cohorts from 0 to 19.1%) for all the outcomes, except for active transport, for which heterogeneity was moderate to high for home facility density ($I^2 = 61.2\%$) and home land use diversity ($I^2 = 77.5\%$). The association between home facility density and active transport, and the association between home building density and moderate-to-vigorous physical activity were driven by BiB and MoBa. The only sex-interaction observed was for the association between distance to green spaces and active transport, where the effect was stronger in girls (β −1.55 min/day, 95 %CI −2.58, −0.51) compared to boys (β −0.23 min/day, 95 %CI −1.24, 0.78; p for interaction 0.02) (**Table A.14**). No education or SES interactions were observed (**Table A.15 and Table A.16**).

The associations between urban environment indicators and active transport remained significant when adjusting for distance from home to school (**Table A.17**). Stratifying by distance from home to school, the estimates for land use within home area and street connectivity within school area were stronger if the school was further from home (β −5.55 min/day, 95 %CI −2.54, −0.56; p for interaction < 0.001, and β −1.38 min/day, 95 %CI −2.41, −0.35: p for interaction < 0.001).

4. Discussion

In this multicohort Europe-wide study, we identified several urban environment characteristics associated with healthy life habits in children. Our findings, which have implications on urban planning policy, suggest that areas of the cities with more vegetation, more building and facility density, less population density and without major roads may be associated with for more physical activity, less sedentary behaviours, more sleep and more active transport.

Our results suggest an increase of physical activity in association with higher vegetation both at home and school, in line with previous studies (Ding et al., 2011; Jansen et al., 2018). However, these associations were weaker in multi-exposure models, indicating a potential

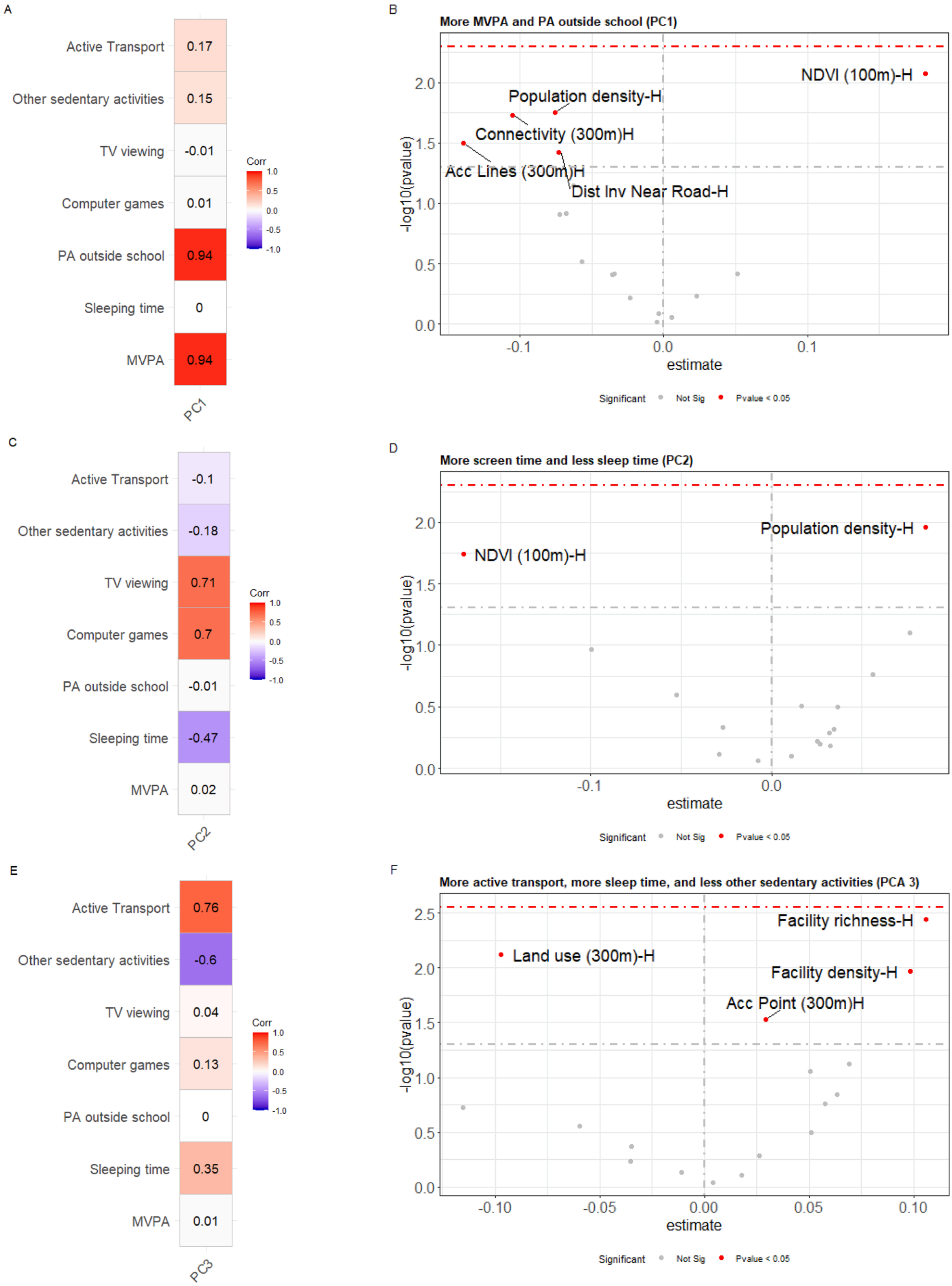

Fig. 2. Association between the urban environment exposures and behavioural patterns in childhood in single-exposure ExWAS model. (A,C,E): Heatmap showing outcome loadings of first three components. Variance explained: PC1 – 26.2%, PC2 – 19.7%, PC3 – 15.3%; (B,D,F): Volcano plots showing significance (*p*-value) against beta coefficient. Black dashed horizontal line at *p*-values of 0.05; red solid horizontal line at TEF of 0.005. Beta estimates for all exposures are shown in **Table A.11**. Model adjusted for cohort, child age, child sex, maternal education, family affluence score and area level SES. Note: Beta coefficient for change in PCs score compared with reference category for the categorical variables. For continuous variables, beta estimates are calculated per interquartile range increase in exposure. Abbreviations: Acc Lines, Accessibility (bus lines-300 m); Acc Point, Accessibility (bus stops-300 m); Dist Inv Near Road, Inverse distance to nearest road; H, Home; MVPA, Moderate-to-vigorous physical activity; NDVI, Normalized Difference Vegetation Index (100 m); PA, physical activity; S, School; TEF, threshold for effective number of test (i.e., *p*-value correction for multiple testing); TV, Television. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Analysis of the association between home exposures, and principal component of health behaviours in childhood (N = 1,581). Multi-exposure model, shown are all exposure variables selected in 10% or more of DSA runs.

	More mvpa and physical activity outside school (PC1)			More screen time and less sleep duration (PC2)			More active transport and more sleep duration, and less other sedentary activities (PC3)		
Home[a]	DSA (%)	Estimate (95% CI)	p-Value	DSA (%)	Estimate (95% CI)	p-Value	DSA (%)	Estimate (95% CI)	p-Value
NDVI-100 m (0.31)	84	0.17 (-0.02, 0.36)	0.08	18	−0.15 (-0.33, 0.03)	0.11	86	0.12 (-0.06, 0.29)	0.21
Green distance (213.25 m)	34	−0.06 (-0.17, 0.06)	0.31	ns			86	**−0.15 (-0.26, −0.05)**	**0.01**
Green spaces Yes (*vs.* No)	ns			10	−0.07 (-0.21, 0.07)	0.31	86	−0.12 (-0.28, 0.04)	0.14
Blue spaces Yes (*vs.* No)	ns			ns			86	−0.08 (-0.25, 0.10)	0.40
Road traffic load-100 m (1,974,930 vehicles/ day m)	ns			ns			ns		
Major roads-100 m (*vs.* no major road)	ns			18	0.00 (-0.12, 0.11)	0.96	82	0.02 (-0.09, 0.13)	0.68
Traffic density on nearest road (11,033.1 vehicles/day)	68	−0.06 (-0.16, 0.03)	0.18	ns			86	0.05 (-0.04, 0.14)	0.30
Inverse distance to nearest road (0.04 m^{-1})	72	−0.06 (-0.13, 0.02)	0.13	ns			82	−0.03 (-0.10, 0.04)	0.37
Population density (7,550.89 people/km^2)	80	**−0.08 (-0.16, 0.00)**	**0.05**	56	0.07 (-0.01, 0.15)	0.07	86	0.05 (-0.02, 0.13)	0.16
Building density-300 m (174,887.9 m^2 built/ km^2)	84	**0.16 (0.05, 0.28)**	**0.01**	12	−0.09 (-0.20, 0.02)	0.12	84	0.04 (-0.07, 0.15)	0.51
Connectivity-300 m (142.38 number of intersections/km^2)	84	**−0.12 (-0.23, −0.01)**	**0.04**	ns			86	0.08 (-0.03, 0.19)	0.14
Accessibility (bus lines-300 m) 1 or more (*vs.* none)	82	−0.13 (-0.28, 0.02)	0.08	ns			78	−0.02 (-0.16, 0.12)	0.76
Accessibility (bus stops-300 m) (17.8 bus stops/ km^2)	58	0.02 (-0.01, 0.05)	0.29	ns			86	0.03 (0.00, 0.06)	0.09
Facility richness-300 m (0.10)	ns			ns			ns		
Facility density-300 m (38.90 facilities/km^2)	22	0.05 (-0.08, 0.18)	0.48	ns			84	**0.15 (0.03, 0.27)**	**0.02**
Land use-300 m (0.19)	ns			ns			86	−0.05 (-0.14, 0.04)	0.29
Walkability index (0.15)	80	0.07 (-0.05, 0.20)	0.26	ns			100	**−0.14 (-0.28, 0.00)**	**0.05**

[a] Reference category as indicated inside brackets for the categorical variables. For continuous variables, estimates are calculated per interquartile range increase in exposure, as indicated inside brackets. Models adjusted for cohort, child age, child sex, maternal education, family affluence score and area level SES. Abbreviations: DSA, Deletion/substitution/addition algorithm; exposures selected in 10% or more DSA runs; MVPA, Moderate-to-vigorous physical activity; NDVI, Normalized Difference Vegetation Index; ns: not selected in the DSA model.

residual co-exposure confounding, for example by population and building density. Time spent on sedentary behaviours was inversely associated with indicators of natural spaces in both the ExWAS and multi-exposure models. This was the case for overall sedentary behaviours and especially for the screen time pattern, consistent with results from a previous Spain-based cross-sectional study that described that children living in homes with more surrounding vegetation had lower probability of excessive screen time (Dadvand et al., 2014). A more recent Spanish cross-sectional study did not find associations between urban environment characteristics and weight-related behaviours in children, including sedentary behaviour and screen time (de Bont et al., 2021).

The results of the multiexposure models showed that greater building density was associated with an increase in physical activity (moderate-to-vigorous and outside the school time) and a decrease in sedentary time in children, in contrast to the null results observed in the single-exposure models. We did not find signs of collinearity, but these results should be interpreted cautiously. The findings regarding building density are consistent with previous studies reporting areas of the cities with more building density related to higher physical activity levels in adults and children (Bringolf-Isler et al., 2014; McGrath et al., 2015). For example, Bringolf-Isler et al., found that higher building density was associated with higher moderate-to-vigorous activity in Swiss children aged 4 to 17 years. In this study, the authors argued that higher building density represents centrally located areas, which are of particular importance for secondary school children (Bringolf-Isler et al., 2014).

In contrast, more population density was associated with lower physical activity outside school hours with no sign of multicollinearity in the models. In our study sites, correlations between building and population density were low-to-moderate, indicating different characteristics of the areas of the cities. In fact, the literature regarding population density and health behaviour shows mixed findings in adults and children (Bringolf-Isler et al., 2014; Buck et al., 2019; Carlin et al., 2017; Saelens et al., 2012; Wang et al., 2019; Xu et al., 2010; Zou et al., 2021). A recent review found 16 studies reporting higher population density encourage more active behaviours, whereas in three studies were inversely associated and eight studies showed null associations (Zou et al., 2021). Interestingly many of the studies reporting positive associations were focused on active transport, indicating that moderate-to-vigorous physical activity and active transport may have different urban determinants. Another reason for the mixed findings could be related to the higher mean population density in European cities compared to American and Australian cities, that most of the evidence is based on, as previously observed by Wang et al. (Wang et al., 2019; Xu et al., 2010). This may suggest that the association between population density and behaviour may be context-specific. Futhermore, more populated areas in Europe may represent areas with more street connectivity and more traffic load, that may be perceived as unsafe, act as barriers and discourage physical activity. In fact, street connectivity at home and school, and proximity to a road also showed an inverse association with physical activity in our ExWAS analysis; however, they attenuated in the multi-exposure models, probably due to confounding by the other exposures. This shows the importance of taking account of multiple exposures in the built environment.

Other built environment characteristic such as facility density and mixed land use were associated with active transport. Mixed land use is usually correlated to greater physical activity in adolescents and adults. Shops and services may stimulate walking in these populations. In children the results are mixed, though (D'Haese et al., 2015; Kerr et al., 2016; Molina-García et al., 2020), and in our study greater land use diversity was associated with less active transport. This age-specific effect of mixed land use was previously described by McGrath, they argued that these areas may be designed for adults, and parents may be concerned for the safety of their children (Aranda-Balboa et al., 2020; McGrath et al., 2015). Another potential explanation for these disparities of result is that some of the studies used perceived mixed land use-access instead of objective measures (Kerr et al., 2016; Vanwolleghem et al., 2016), and perception of the land use may play a major role as shown by Cerin et al., in their mediation study (Cerin et al., 2018). Moreover, the mixed-land use indicator may not represent more facilities. In fact, facility density was positively associated with active transport in our study.

Living closer to a major road was associated with shorter sleep duration in childhood in our study. This is likely an indirect association and the most probable mechanism explaining this association is the noise generated by the traffic that affects the quality and duration of the sleep in children and adults (Basner and McGuire, 2018). This finding reinforces the previous findings on the harmful effects of traffic on sleep that can lead to behavioural problems (Tiesler et al., 2013). Traffic-related exposure patterns, including higher levels of road traffic, noise and air pollution, have also been related to childhood obesty risk, with sleep being one possible mechanism (de Bont et al 2021).

Our study has several main strengths. First, our comprehensive evaluation of health behaviours goes beyond most other studies which only included physical activity, and also included the evaluation of other behavioural domains (e.g. screen time and sleep) and of their combination. Second, we used of a broad range of built environment exposures based on geospatial modelling using home and also school addresses; these objective measures reduce the potential bias of self-reported measures, compared to previous research. Third, we used qGIS as a novel tool to obtain an objective measure of active transport from home to school. Fourth, this study is based on a set of complementary statistical approaches based on previous simulation studies including the ExWAS method, characterized by a high sensitivity and low false-negative rate, and the DSA method with a low false-positive rate and takes into account the potential confounding by multiple exposures (Agier et al., 2016). Last, our study was performed in six different cohorts across Europe, which allowed us to use comparable variables across diverse countries and to describe the child health behaviour patterns across Europe and test if the associations are robust in all the cohorts. This is especially relevant since previous research has been focused mainly in the United States and Australia where city design is different from Europe.

This study also has several limitations. First, we used subjective measures of behaviours based on questionnaires, except for active transport. The age range included in this study is from 6 to 11 years, and parents may not be aware of their offspring's behaviours especially of the oldest children in this study, and their perception may affect the quantification of the physical activity and other behaviours (Verbestel et al., 2015). However, the variations in behavioural patterns observed between our 6 cohorts did not appear to be easily explained by age or geographical location of the cohort (e.g. northern *vs* southern European cohorts). Future studies may consider the inclusion of objective measures, such as devices to estimate sleep duration and sedentary activity. Second, this study is cross-sectional. Longitudinal designs could allow for studying the change in urban environment domains and their impact on health behaviours and improving any causal interpretation of the results. Third, this study can be affected by self-selection bias, for example families who like physical activity may choose to live closely to high vegetation areas. Fourth, levels of measurement error may be different among the exposures, and we did not attempt to correct for these differences in this study. Five, residual confounding is possible. Even though we have taken into account different measures of SES in the analysis, there may be unmeasured social factors related to the neighbourhood self-selection and awareness of healthy behaviours (Lamb et al., 2020). However, results were robust when adjusting for family affluence score and area level SES, and when stratifying by maternal education and area level SES. Therefore, any potential residual confounding is expected to have little effect. Finally, we recognize that the small HELIX subcohort (N around 200 in each country) is unlikely to be representative of the general population in each country, both in terms of health behaviours and in terms of the spatial areas covered; this limits the generalisability of results, as well as our ability to compare across different cities. We therefore recommend follow up of these findings in larger pan-European studies.

A high proportion of the children included in this study (63.6%) did not meet the current WHO guidelines for moderate-to-vigorous physical activity and 58.6% spent more than two hours per day watching TV or playing computer and video games (World Health Organization, 2020). These proportions are higher than the figures reported by WHO European Childhood Obesity Surveillaince Initiative for children of similar age range (20.6% and 38.2%, respectively)(Whiting et al., 2021). Futhermore, active transport was considerably low, being the daily average time spent from home to school of 6.9 min.

Our results highlight the importance of early life environmental exposures on establishing risk factors for subsequent NCDs. Public health interventions tend to focus on influencing individual behaviours rather than tackling the wider system determinants that drive these behaviours and widen health inequalities. Our evidence reinforces the need for policymakers to prioritise urban design to improve children's health-promoting behaviours and prevent adult ill-health. This is very cost-effective as it requires single investment that affect large number of people over time, as compared to school based physical activity interventions for instance (Zapata-Diomedi et al., 2019). Our study found the relationship between built environment and health behaviours to be similar across the cohorts in six countries, indicating investment in health-promoting urban design may benefit children's health across Europe (Sallis et al., 2016). Our study also indicates that these designs need to be comprehensive and take into account several urban indicators. One of the strategies should be improving vegetation in the streets and green spaces. If they are more attractive and well maintained, it may improve the perception of safety of parents and children (Kruize et al., 2019). One of the most common strategies is to promote active commuting and public transportation use. Even though we did not observe an association between transport accessibility and health behaviour in childhood, this initiative may be positive to reduce traffic load and the subsequent air pollution and noise.

Future research is needed, including other urban indicators that may be relevant for children and adolescent behaviours (such as: pedestrian zones and sport facilities (e.g. tennis table and volleyball courts)), the combination of perceived and objective measures of the urban environment (such as crime and attractiveness), the use of objectively measures of health behaviours, including more countries from Eastern Europe and other areas less studied, and implement longitudinal studies and intervention studies to assess the change in the urban environment and its impact on lifestyle (Aranda-Balboa et al., 2020; Smith et al., 2021).

5. Conclusions

This comprehensive and systematic study suggests that more vegetation, more building and facility density, less population density and greater distance from major roads may be associated with health-promoting behaviours in childhood. These findings reinforce the importance of urban design in promoting a healthier future for children.

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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***Data** sharing*

Deidentified participant data will be made available to researchers conditionally upon receipt of an approved study proposal along with evidence of approval of the proposal by the HELIX committee and an accredited ethics committee. Proposals should be made by email to the corresponding author. To gain access, data requesters will need to sign a data access agreement.

Contributions

SFB, OR and MV contributed to the study conceptualisation and methodology. MN, LC, MV, RG, BH, JW and MV acquired the funding. SFB and SM did the formal analyses. SFB, OR and MV interpreted the results. SFB wrote and prepared the original draft. OR, SF, SM, XB, JdB, MdC, DDG, LM, MN, DR, JU, LC, MI, MV, RG, AD, SA, GMA, JE, NHK, JL, BH, JW, RMcE, FS, PV and MV revised and edited the manuscript. SM accessed and verified the data. All authors read and approved the final version of the manuscript. All authors had full access to all the data in the study and had final responsibility for the decision to submit for publication.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2022.107319.

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