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Towards healthy school neighbourhoods: A baseline analysis in Greater London

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ABSTRACT

Creating healthy environments around schools is important to promote healthy childhood development and is a critical component of public health. In this paper we present a tool to characterize exposure to multiple urban environment features within 400 m (5–10 min walking distance) of schools in Greater London. We modelled joint exposure to air pollution (NO_2 and $PM_{2.5}$), access to public greenspace, food environment, and road safety for 2,929 schools, employing a Bayesian non-parametric approach based on the Dirichlet Process Mixture modelling. We identified 12 latent clusters of schools with similar exposure profiles and observed some spatial clustering patterns. Socioeconomic and ethnicity disparities were manifested with respect to exposure profiles. Specifically, three clusters (containing 645 schools) showed the highest joint exposure to air pollution, poor food environment, and unsafe roads and were characterized with high deprivation. The neighbourhood of the most deprived cluster of schools had a median of 2.5 ha greenspace, 29.0 $\mu g/m^3$ of NO_2, 19.3 $\mu g/m^3$ of $PM_{2.5}$, 20 fast food retailers, and five child pedestrian crashes over a three-year period. The neighbourhood of the least deprived cluster of schools had a median of 21.8 ha greenspace, 15.6 $\mu g/m^3$ of NO_2, 15.1 $\mu g/m^3$ of $PM_{2.5}$, 2 fast food retailers, and one child pedestrian crash over a three-year period. To have a school-level understanding of exposure levels, we then benchmarked schools based on the probability of exceeding the median exposure to various features of interest. Our study accounts for multiple exposures, enabling us to highlight spatial distribution of exposure profile clusters, and to identify predominant exposure to urban environment features for each cluster of schools. Our findings can help relevant stakeholders, such as schools and public health authorities, to compare schools based on their exposure levels, prioritize interventions, and design local policies that target the schools most in need.

1. Introduction

The urban environment can affect our health and wellbeing from early life. Health inequalities can emerge in childhood due to unequal access to healthy environments and continue to impact across the life course (Villanueva et al., 2016). Children growing up in neighbourhoods with high concentrations of NO_2 and $PM_{2.5}$ showed a loss of 5% in their lung capacity over a five-year period, increasing the risk of lung diseases in adult life (Mudway et al., 2019). Low access to greenspace during childhood increased the risk of developing a psychiatric disorder up to 55% (Engemann et al., 2019). High exposure to greenspace during childhood was linked to increased physical activity, decreased risk of obesity, and improved cognitive and behavioural development (Dadvand et al., 2019; Islam et al., 2020). Neighbourhoods' characteristics including junction density and vehicle flow density were influential in increasing child pedestrian casualties (Green et al., 2011). Built-environment features such as land use diversity and road configurations (e.g., speed limit) showed to affect child pedestrian crashes (Rothman et al., 2014; Yu, 2015). Many other studies that investigated the impact of urban environment features also highlighted the role of easy access to fast food on obesity (Burgoine et al., 2018; Han et al., 2020; Pineda et al., 2021), exposure to air pollution on cognition (Sunyer et al., 2015), and access to nature on mental and physical health (Maes et al., 2021; van den Bosch et al., 2018).

Schools and their immediate neighbourhood are places where children spend the most time outside their homes. Therefore, these settings have a crucial role in providing equitable and healthy environments for children, particularly in disadvantaged communities where children's residential neighbourhood is strongly affected by income deprivation (Christian et al., 2015). However, the location of schools and their neighbourhood characteristics generate differential levels of exposure to hazardous (such as air pollution) and health-promoting (such as ac-

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cess to parks) factors that can create and widen health inequality. Schools located in proximity of roads, river transport, underground stations, bus stops, and traffic lights are more likely to breach the WHO air quality guideline for NO_2, while those situated in neighbourhoods with less traffic congestion and more green space are more likely to have a better air quality (Shoari et al., 2021b). In terms of access to greenspace, research showed that schools located in the central areas of London were less likely to have a public park in their immediate vicinity (Shoari et al., 2021a). As indicated by (Jacobs et al., 2021a), access to greenspace in schools' neighbourhoods is associated with socioeconomic status such that schools in affluent areas are more walkable and have more access to greenspace compared to their peers. As a result, children are more likely to adopt active modes of travel to and from school (Jacobs et al., 2021b). With respect to food environment, studies argued that a greater availability of unhealthy food retailers in school neighbourhoods affects dietary intake of children (Shareck et al., 2018; Smith et al., 2013) although more research is needed to understand how that relates to Body Mass Index (BMI) (Williams et al., 2015). The built-environment characteristics around school can also affect child pedestrian crashes. For example, schools located in neighbourhoods with more intersections, higher density of one-way street, and with more commercial land use can increase the rate of crashes (Rothman et al., 2017).

Variations in exposure to urban features is often related to socioeconomic gradient. For example, evaluating the air quality of schools in England showed that schools in areas with high annual mean concentration of $PM_{2.5}$ have significantly higher proportions of pupils from economically disadvantaged and ethnic minority background (Osborne et al., 2021). Exposure to fast food retailers in a neighbourhood was found to be associated with household income (Burgoine et al., 2018). More than 50% of the schools in United States with a majority of pupils from low-income families and Hispanic background have a fast food retailer nearby, while this figure reduces to 21% in schools with a majority of White pupils (D'Angelo et al., 2016).

An increasingly popular solution to reduce health inequalities has been place-based public health programmes that are tailored to priorities and specific issues of communities. Since place-based programmes aim to improve health by changing environments, they can lead to strong and lasting effects on health (Kondo et al., 2015). An example of these programmes targeting children is the "school superzone" initiative, implemented in 13 local authorities of Greater London. This initiative aims to create healthier environments in the 400 m radius around schools by identifying what features makes the school unhealthy and to implement corrective interventions, depending on local needs and circumstances. The focus of this initiative includes tackling issues such as childhood obesity, reduced physical activity, air pollution, limited access to greenspace, and unsafe routes to schools. More details on the school superzone can be found in (Catt and Senior, 2020; Yvonne Doyle, 2019). Most studies related to this initiative have been qualitative based on audits of local authority officers.

An important component toward creating healthy environments around schools is gathering comprehensive evidence on simultaneous exposure to various urban environment features including air quality, access to greenspace, food environment, road safety, among others. The ability to recognize the subgroups of schools with similar exposure patterns (i.e., exposure profiles) becomes valuable as it enables us to understand distinct exposures, their spatial distribution, and how those relate to the socioeconomic characteristics. Additionally, exposure profiles can be linked to health outcomes to assess their risk levels, which is an essential step toward targeted implementation of interventions to reduce harmful exposures and increase beneficial ones.

Studies that have considered exposure to multiple urban environmental factors are limited. For example, Doiron et al. (Doiron et al., 2020) explored spatial patterns of exposure to multiple environmental factors within three Canadian cities and identified health promoting and health damaging areas of cities in terms of greenness, concentrations of NO_2, and walkability. Yet, no comprehensive study has uncovered school-level exposure with respect to multiple urban environment features and their spatial distribution across a large metropolitan area like London. This research aims to fill this gap by i) identifying the latent clusters of schools with similar exposure profiles within their 400 m buffer, ii) characterizing each cluster, and iii) comparing each school exposure to the "median London schools" defined as median value of exposures in London. We also explore associations between clusters characteristics, ethnicity, and socioeconomic status.

2. Materials and methods

2.1. Study area

We were interested in studying school neighbourhood environment and thereby considered a 400 m circular buffer around school boundary in Greater London. The 400 m buffer was selected in accordance with the "School Superzone" initiative and corresponds to 5–10 min of walking. We identified the location and the extent of grounds of educational establishments in Greater London using Ordnance Survey Sites Layer (version April 2020) available from https://digimap.edina.ac.uk/. Ordnance Survey is a UK-based agency that provides detailed and up-to-date digital maps. We considered schools with pupils aged from 5 to 16 years and excluded schools that solely functioned as nursery, children centre, college, or university. We identified 32 duplicated school polygons that were removed from data. These were school polygons that were identical but were referring to two separate institutions, for example, primary school and high school under the same establishment names. Our final data included 2,929 schools in Greater London in 2020.

2.2. Urban environment features surrounding schools

Based on previous literature, we hypothesize that built and environmental features, including air quality, access to greenspace, food environment, and road safety exert influence on health and well-being of school-age children. For exposure to air pollutants, we estimated the mean annual concentration of NO_2 and $PM_{2.5}$ within 400 m buffer around each school. Air pollutant data was generated from the Community Multiscale Air Quality (CMAQ-urban) model (Beevers et al., 2012; Beevers et al., 2013), which uses emission data from the London Atmospheric Emission Inventory (LAEI) () in combination with the Weather Research and Forecasting meteorological model (Wang et al., 2008), the Community Multiscale Air Quality model (Byun, 1999), and the Atmospheric Dispersion Modelling System roads model (Cambridge Environmental Research Counsultants CERC, 2014). The LAEI provides emission data at 20x20 m resolution across London local authorities. This inventory includes emissions from key industrial, commercial, domestics, and transport sources such as large boiler plants, gas heating, agricultural and natural sources, rail, ships, airports, etc. The CMAQ-urban model output was processed to provides annual average concentrations of NO_2 and $PM_{2.5}$ concentrations in 2013 at a spatial resolution of 20x20 m over the Greater London. After intersecting 400 m school buffer polygons with concentration data grid, we calculated the average concentration in each school buffer zone. Fig. 1 in Supplementary Material shows a map of annual average NO_2 and $PM_{2.5}$ in the study area.

Various measures of greenspace have been used in previous studies. These included the normalized difference vegetation index (NDVI), urban vegetation such as garden and parks, natural vegetation components such forested and agricultural areas (Dadvand et al., 2015; Engemann et al., 2019; Putra et al., 2020). In this research, we consider greenspace sites that are relevant for school-age children. Data on greenspace was provided by the Open Spaces product of Greenspace In-

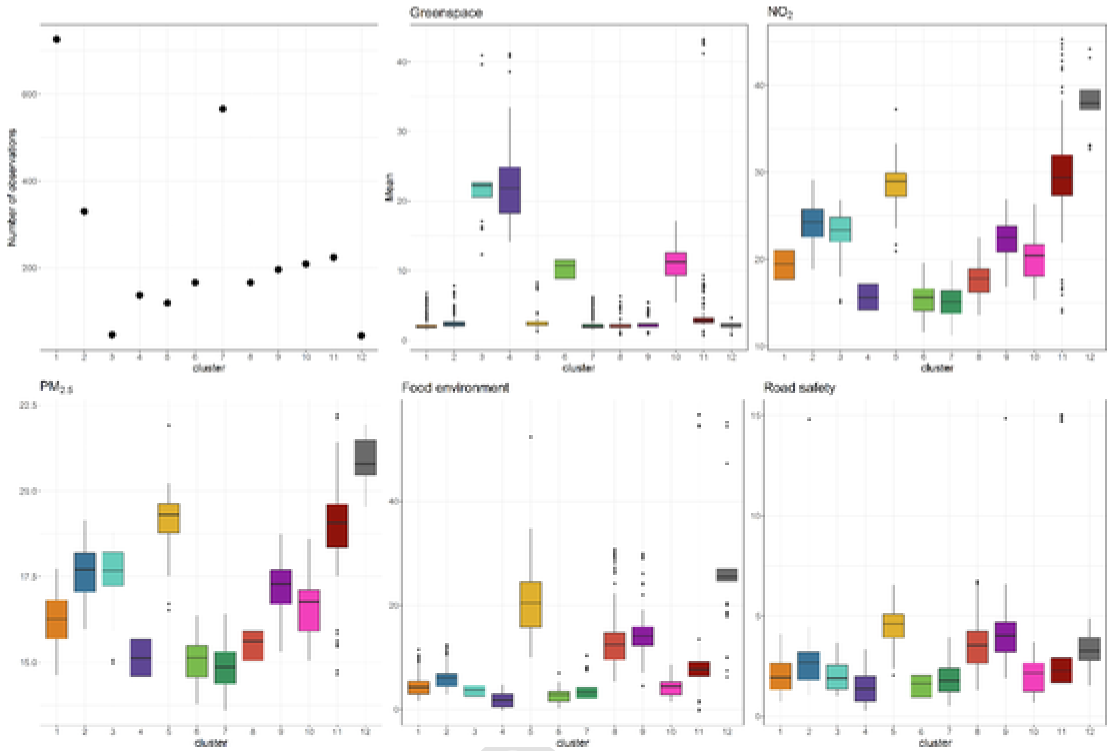

Fig. 1. Characteristics of identified clusters.

formation for Greater London (GiGL) who collates and manages data on public greenspace in London (Greenspace Information for Greater London, 2017). Information comes in the form of a polygon dataset. We only considered polygons with land use typology labelled as “Parks and gardens”, “Children and Teenagers” (e.g., play space, and playgrounds), and “Natural and Semi-natural Urban Greenspace” (e.g., public and private woodland, common). Our assessment of access to greenspace was based on intersecting school 400 m buffers with GiGL data and calculating the total area (ha) of public greenspace within those buffers. Fig. 2 of supplementary material shows the location of greenspace sites considered in this study.

Geocoded information on food retailers was extracted from Ordnance Survey Point of Interest (version 2020) available from https://digimap.edina.ac.uk/. To assess unhealthy food environment around schools, we included food retailers that were labelled as “Fast Food and Takeaway Outlets” and “Fish and Chip Shops”. This resulted in the inclusion of global large chains, local chains, as well as independent small shops. However, since there is no consistent definition of fast food retailers across previous studies, we might have not included other poten-

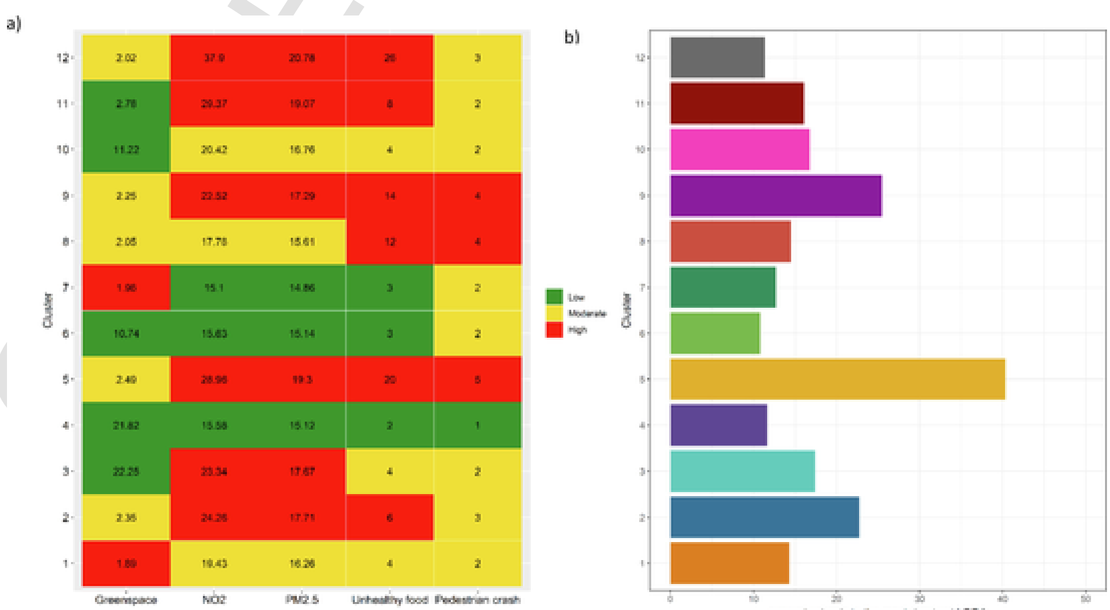

Fig. 2. a) Heatmap of urban environment features for each cluster categorized in low, moderate, and high exposure based on the tertiles of the exposures (each tile contains the posterior median of the cluster value for the corresponding variable), and b) mean percent of schools located in the most deprived LSOAs for each cluster. Note that since exposure to greenspace is beneficial, we reversed the order of categorization.

tial sources of unhealthy food environments such as convenience stores. For example, other sources of unhealthy food environment in other studies included convenience and general stores and confectioners (Cetateanu and Jones, 2014; Oishi et al., 2021). We intersected the school environment polygons and fast food data and calculated the total number of fast food retailers for each school buffer. Location of fast food retailers is shown in Fig. 3 of Supplementary Material. Alternatively, other measures of food environment such as the proportion of fast food retailers to all food establishments in an area (Shareck et al., 2018), density of fast food retailers over a certain area (Wall et al., 2012), and the distance to the closet fast food retailer (Han et al., 2020) could be considered.

We used the number of child pedestrian crashes within 400 m buffer of schools, as a proxy measure to assess road safety. To this end, we used crash incidents obtained from Department for Transport, which collects information from STATS19 accident report form, containing information on the geocoded location of crashes, type of vehicle involved, circumstances of personal injury, and the consequential casualties. To account for the yearly fluctuation in crash incidents, data over a period of three to six years is usually considered (Hauer, 1997). In this study we used the total crash counts over a period of three years (2017–2019). Note that this input only includes crashes on public roads that are reported to the police, and therefore are registered using the STATS19 form. We then restricted the data to entries identified with pedestrians less than 15 years old. We excluded observations for which age of casualty was not recorded (~2% of total data). Spatial distribution of child pedestrian crashes is illustrated in Fig. 4 of Supplementary Material.

2.3. Socioeconomic confounders

We adjusted the model for potential socioeconomic confounders at Lower Super Output Area (LSOA) level. LSOAs are geographical units in England used to report small area statistics. Each LSOA contains between 400 and 1,200 household or 1,000 and 3,000 population. The confounders included were the percentage of population from Black, Asian, and Minority Ethnic groups obtained from 2011 UK Census , and the quantiles of index of multiple deprivation in 2019 provided by the Ministry of Housing, Communities and Local Government (available from https://data.london.gov.uk/dataset/indices-of-deprivation). In the UK, the index of multiple deprivation is a relative measure of deprivation across small areas. It is a weighted combination of seven domains: income, employment, health and disability, education, skills and training, barriers to housing and services, living environment, and crime. We assigned to each school the confounder data of the LOSA in which the centre of the school polygon fell into.

2.4. Statistical analysis

We used a nonparametric Bayesian clustering method that relies on Dirichlet process mixture models (DPMM) while adjusting for socioeconomic confounders. The DPMM can be seen as an extension of mixture model with infinite components, where the number of components (i.e., clusters) is assumed to follow a Dirichlet process and is inferred from the data (Antoniak, 1974; Ferguson, 1973). As a dimension reduction method, the DPMM can deal with collinearity of simultaneous exposure to multiple factors (Liverani et al., 2016), which is the case in this study. Some applications of the DPMM can be found in detail in (Coker

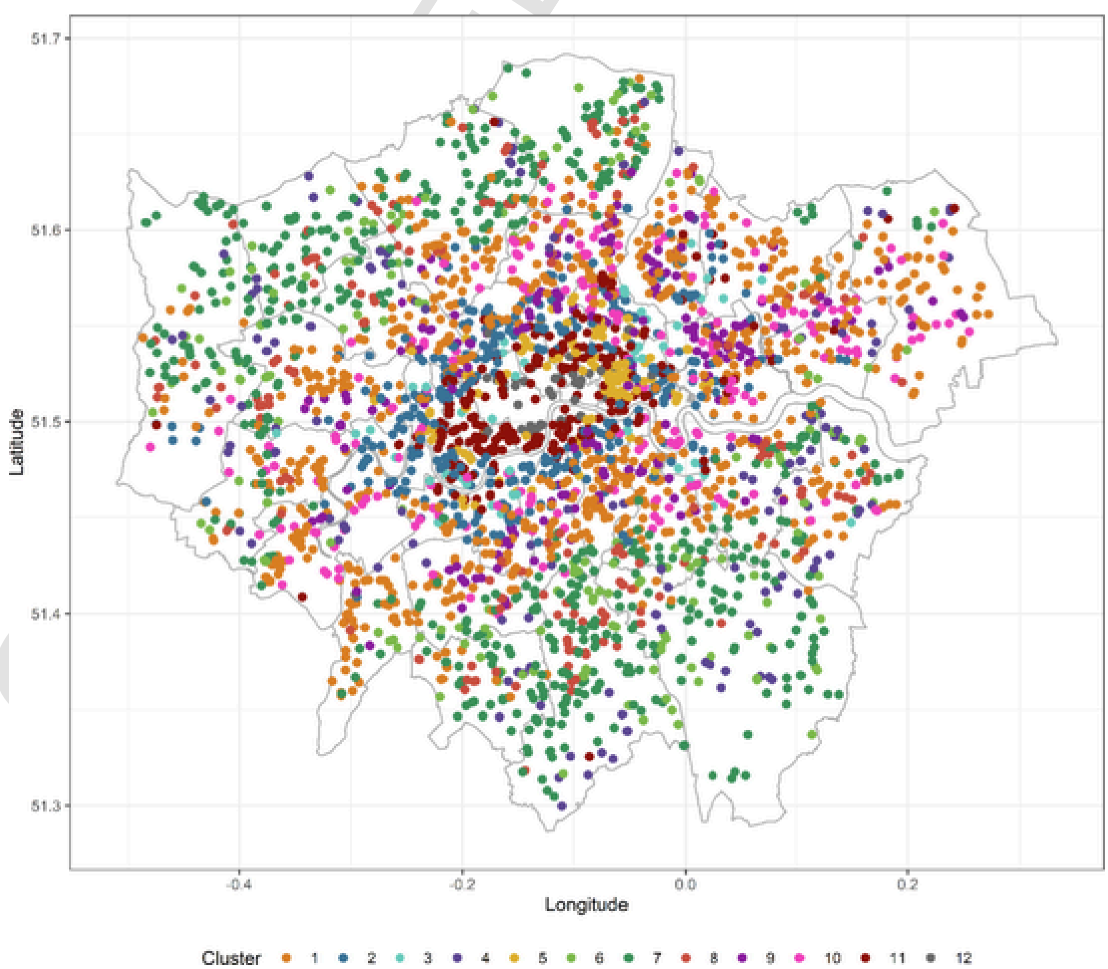

Fig. 3. Map of identified clusters of school neighbourhoods in Greater London.

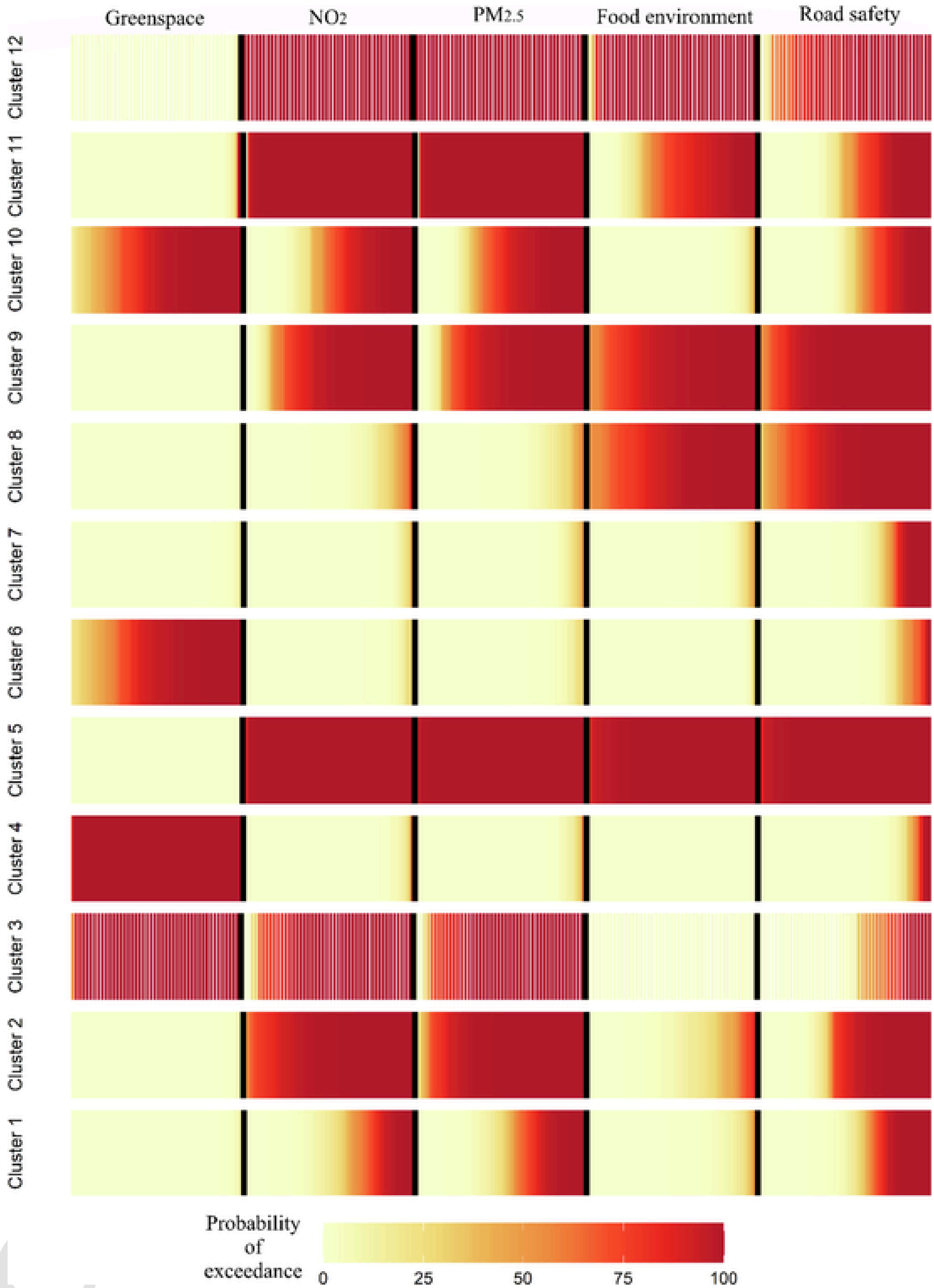

Fig. 4. Probability of exceeding the median exposure for each urban feature at each school. The probability of exceedance for each school is represented with a line.

et al., 2017; Coker et al., 2016; Heydari, 2018; Lavigne et al., 2020; Papathomas et al., 2011).

In this study we are interested in clustering schools based on a set of specific urban environment features (NO_2, $PM_{2.5}$, greenspace, number of unhealthy food retailers, and child pedestrian crash) within a 400 m school buffer. We standardized data for each feature by subtracting the mean and dividing by the standard deviation. Let $y_{i,1}$, $y_{i,2}$, …, $y_{i,5}$ be the standardized measure of exposure to the five urban environment features for the i^{th} school buffer, where i = 1, 2, …, 2,929. Following the model specification in (Gershman and Blei, 2012; Görür and Edward Rasmussen, 2010), we can describe $y_{i,q}$ (q = 1,2,…,5) as a mixture of normal distribution with K components.

$$y_{i,q} = \sum_k \pi_k N(y_{i,q} \mid \mu_{k,q}, \tau_q) + X_i\beta \tag{1}$$

where π_k is the weight of the k-th component in the mixture of Normal with cluster-specific mean, $\mu_{k,q}$, and precision (inverse variance) τ_q,

X_i denotes the vector of confounders (i.e., percent black, Asian, and minority ethnicity, and IMD quantile) with their associated vector of coefficients β. We introduce an allocation variable C_i that indicates to which cluster the ith school exposure belongs to and this can take any value between 1 and K. We can rewrite the equation (1) as.

$$y_{i,q} \sim \; N\left(\mu_{C_i,q}, \tau_q\right) \tag{2}$$

$$C_i \mid \pi \sim \; Discrete\left(\pi_1, \cdots, \pi_K\right) \tag{3}$$

$$\pi \mid \alpha \sim Dirichlet\left(\frac{\alpha}{K}, \cdots, \frac{\alpha}{K}\right) \tag{4}$$

$$\mu_{k,q} \sim \; N\left(m_{o,q}, T_{o,q}\right) \tag{5}$$

where the Dirichlet process is defined with two parameters: a baseline distribution (a Normal density with mean $m_{o,q}$, and precision, $T_{o,q}$) and a concentration parameter α, which expresses the strength of the belief in the baseline distribution. Since drawing inference with an infinite number of components is computationally cumbersome, we considered a truncation to limit the number of clusters. In this paper, we define K = 20, which we found to be sufficiently large for the purpose of our application. For details regarding the DPMM and its implementation see (Ferguson, 1973; Gershman and Blei, 2012; Li et al., 2019; Ohlssen et al., 2007; Wehrhahn et al., 2018). For a better interpretability, we back-transformed the results to the original scale.

With respect to prior specification, we specified a non-informative Normal (0, 100) prior distribution for $m_{o,q}$ and the effect of the confounders β, a Gamma (1,1) for α, and a Gamma (0.01, 0.01) for the precision parameters $T_{o,q}$ and τ_q. Inference was performed through Markov Chain Monte Carlo (MCMC) simulations in the NIMBLE Package in R (de Valpine et al., 2017). The posterior inferences for model parameters were obtained from two chains with 70,000 iterations and the first 30,000 iterations were discarded to ensure convergence. We considered a thinning factor of 5 as a way to reduce auto-correlation. We checked the convergence of the parameters using the Gelman-Rubin statistic (Gelman and Rubin, 1992) and visually using trace plots.

We performed a sensitivity analysis to evaluate how robust the posterior estimates are under different model specifications. We considered four model scenarios: in scenario 1, we repeated our analysis using the 2019 LAEI pollution emission data. In scenario 2, we evaluated the effect of changing priors on the estimates of model parameters. Specifically, we considered a Gamma (1,0.01) for the precision parameters $T_{o,q}$ and τ_q and then a uniform prior distribution, uniform(0, 10), on their standard deviations $\sigma_{o,q}$ and σ_q (defined as $\sigma_{o,q} = (T_{o,q})^{-1/2}$ and $\sigma_q = (\tau_q)^{-1/2}$). In scenario 3, we evaluated the effect of changing the prior on the concentration parameter α by considering a uniform prior distribution, uniform(0.3, 10). Finally, in scenario 4, we increased the maximum number of component K to 30.

2.5. Characterization of clusters of exposure profiles

A well-known issue of MCMC algorithms in Bayesian mixture models is label switching (Jasra et al., 2005; Stephens, 2000), which refers to the possible change of the label of the cluster allocation parameter, C_i, from iteration to iteration of sampler. As a consequence of this feature, the interpretation of clusters is not straightforward and requires other methods to optimally partition the data. A possible solution to this problem relies on the construction of a posterior similarity matrix, followed by the application of a classical hierarchical clustering, distance-based partitioning algorithm (e.g., partition around the medoid (PAM) (Kaufman and Rousseeuw, 2009)), or minimizing the posterior expectation of some loss function (e.g., Binder's method (Binder, 1978; Fritsch and Ickstadt, 2009)). For our dataset of size N (N = 2,929 in this study), the posterior similarity matrix S was an N × N matrix, where each element represents the pairwise probabilities that two schools belong to the same cluster. For details on how to construct the posterior similarity matrix S, see (Medvedovic and Sivaganesan, 2002; Molitor et al., 2010; Ohlssen et al., 2007). Adopting the procedure used in (Gilholm et al., 2020; Pirani et al., 2015), we applied the PAM algorithm on the similarity matrix S to identify the number of clusters that provided the optimal partitioning of data. This was determined based on the comparison of the average silhouette width for different number of clusters ranging from 2 to 20. The average silhouette is computed using the average distance between observations of the same cluster. It gives an indication of the quality of clustering, with a large silhouette indicating a good clustering.

Once the optimal number of clusters was selected, we characterized clusters and evaluated the uncertainty associated with each cluster under the optimal partitioning of data. To characterize each cluster, we computed summary statistics of observations assigned to each cluster. To compare clusters in terms of exposures, we summarized the predominant urban environment features for each cluster by computing the median exposure of each feature and comparing it to the tertiles of exposure for that feature in all schools. Doing so allowed us to categorize exposures into "high", "moderate", and "low" exposure. This approach has been used in (Coker et al., 2017) and (Liverani et al., 2016) as well. Finally, we investigated the associations between exposure levels and socioeconomic status.

To estimate the uncertainty associated with each cluster, we used the posterior distribution of μ_k and computed the standard deviations of μ_ks that were allocated to the same cluster (identified by PAM) across the entire MCMC sample. In other words, if the model is capable of consistently partitioning the data from iteration to iteration, we expect that cluster assignment of schools are similar throughout the iteration, leading to similar values of μ_ks in each cluster. As a result, we obtain a posterior distribution of μ_ks with small standard deviation, meaning that the number of clusters selected with the PAM algorithm ensures the optimal partitioning of observations. This approach has been adapted from (Molitor et al., 2010).

2.6. Benchmarking of schools' exposure profiles

For a more effective identification of high priority individual schools, we benchmarked school exposure in relation to median exposure of London's schools. Specifically, we estimated the probability of exceeding the median exposure to greenspace, NO_2, $PM_{2.5}$, unhealthy food environment, and road safety for each school.

3. Results

Descriptive statistics of the urban environment features surrounding schools are reported in Table 1.

3.1. Identification and characterization of clusters

We identified 12 clusters of school exposure profiles using the PAM algorithm on the similarity matrix. In terms of evaluating the uncertainty associated with each cluster, we employed the entire MCMC sample and calculated standard deviation of observations in a given cluster over 8,000 iterations. Generally, the specified model resulted in clusters with small standard deviation, giving confidence in the optimal parti-

Table 1
Descriptive statistics of urban environment features within 400 m buffer of schools.

Risk factors (urban features)	Mean (standard deviation)	Median	Min	Max
Annual average NO_2 (μg/m^3)	20.3 (6.2)	19.6	8.3	53.5
Annual average $PM_{2.5}$(μg/m^3)	16.5 (1.8)	16.2	12.7	23.4
Public greenspace (ha)	4.7 (6.7)	2.0	0.0	62.6
Fast food retailer	6.6 (7.7)	4.0	0.0	82.0
Child pedestrian crash	2.4 (2.3)	2.0	0.0	21.0

tioning of data. Posterior average and posterior interval estimate of the identified clusters are depicted in Fig. 1. Fig. 1 also includes the number of schools that were allocated to each cluster. Clusters 3 and 4 exhibited considerably high access to public greenspace, with the mean area of greenspace about two- to ten-fold higher than that of other clusters. With respect to air pollution, the mean concentration of NO_2 and $PM_{2.5}$ in all clusters exceeded the WHO-recommended concentrations of 10 μg/m^3 and 5 μg/m^3, respectively. Furthermore, clusters 5, 11 and 12 contained schools with particularly high levels of air pollution, up to 53.5 μg.m^{-3} for NO_2 and 23.4 μg.m^{-3} for $PM_{2.5}$. The food environment within 400 m buffer of schools was highly variable across clusters, with clusters 4 and 12 being the two extreme situations with an average of two and 26 fast food retailers, respectively. In terms of road safety, schools in clusters 5, 8, and 9 showed a higher number of child pedestrian crashes around schools compared with other clusters. Schools in these clusters had on average four crashes involving a pedestrian child over a period of three years. Cluster 11 included a handful of outliers, in which there were schools with exceptionally high values with respect to a single factor such that they could not be allocated to any other cluster. Partitioning the similarity matrix with higher numbers of clusters could result in the separation of these outliers in favour of creating new but depopulated clusters.

In terms of results of sensitivity analyses, the results were consistent, and we observed a similar spatial clustering pattern. In addition, we observed similar estimates of model parameters under the considered scenarios (Table 1 of Supplementary Material). To help with the interpretation and comparability of cluster-specific exposure levels, the heatmap shown in Fig. 2-a displays the level of exposure to each feature in each cluster. If the median exposure to a factor (NO_2, $PM_{2.5}$, fast food environment, and road safety) fell in the lower, middle, and upper tertile, we labelled that factor as “low exposure”, “moderate exposure”, and “high exposure”, respectively. Since access to green space is a beneficial feature of an urban environment, the order of categorization criteria has been inverted. Fig. 2-a indicates that clusters 4 and 6 contained schools with low to moderate exposures with respect to all NO_2, $PM_{2.5}$, unhealthy food environment, and road crashes and high exposure to greenspace. In contrast, clusters 5 and 9 were categorized as high exposure to harmful features except greenspace, meaning that schools in these cluster are experiencing above the average levels of exposure.

When evaluating associations with socioeconomic status (Fig. 2-b), we observed clear disparities of exposure. Cluster of schools in the most deprived areas had generally moderate to high exposure to harmful features. Specifically, road safety showed to be one of the predominant risk factors in clusters 5 and 9 compared to other clusters, where the percent of schools in the most deprived area was the highest. A similar pattern was observed when we related the heatmap of clusters to the median percent of population from Black, Asian, and Minor Ethnicity groups (Fig. 5 in Supplementary material). Clusters 1, 4, 6, 7, and 10, which generally had low to moderate exposure to air pollutant, unhealthy food environment, and road crashes and moderate to high exposure to greenspace, showed to have a relatively low percent of schools in deprived areas as well as low percent of population from Black, Asian, and Minority groups.

Fig. 3 represents spatial location of schools and their cluster allocation. Schools located in suburban areas of London (mainly clusters 4, 6, and 7) were generally allocated to clusters with low and moderate exposure to harmful and moderate to high exposure to beneficial features. On the other extreme end, schools with the highest levels of air pollution and unhealthy food environment were mostly located in central parts of London (clusters 2, 3, 5, 11, and 12). We identified hotspots for child pedestrian road crashes mainly in south and central London, specifically in areas with high levels of deprivation (clusters 5, 8, and 9). Schools in clusters 1 and 10, characterized as moderate exposure with respect to all factors, were mostly located in less deprived areas in South-West and on the edge between central and suburban London.

3.2. Benchmarking schools’ neighbourhood exposures

Fig. 4 shows the probability of exceeding the median exposure to each urban feature for each school in London. The median exposure was calculated as two ha for greenspace, 19.6 μg/m^3 for exposure to NO_2, 16.2 μg/m^3 for $PM_{2.5}$, four fast food retailers for food environment, and two crashes for road safety. We can clearly see contrasting patterns of probabilities of exceedance in schools belonging to the clusters with high exposure to NO_2, $PM_{2.5}$, unhealthy food environment, and road crashes (e.g., cluster 5) versus the clusters that have low exposure to these harmful features (e.g., cluster 4). Fig. 4 also allowed us to distinguish the transitioning clusters (e.g., cluster 1 and 10), containing schools with exposure profile that can overlap with other clusters. In fact, the transitioning clusters contained schools with both high and low probabilities of exceedance at the same time.

4. Discussion

We used a class of Bayesian nonparametrics method to identify distinct clusters of schools with similar exposure patterns to multiple factors, understand exposure levels for each cluster, and tease out the dominant contributor exposure in each cluster. Our study includes a baseline analysis of subgroups of schools with similar air pollution, access to public greenspace, number of fast food retailers, and pedestrian child crashes within 400 m (equivalent to 5–10 min of walking) of their boundaries. We standardized the exposure data before performing the analysis to ensure that all features had an equal influence over the results. This should not substantially change our cluster allocation pattern since the focus was on understanding the clusters of schools with similar simultaneous exposures to multiple factors. However, it becomes of importance in the case that exposure profiles are linked to a health outcome.

The median concentration of air pollutants in all clusters were above the WHO-recommended air quality guideline, and six clusters exhibited considerably high exposure to air pollution, which included 33% (equivalent to 959) of London schools. These were located in central boroughs or in the most deprived neighbourhoods of London. Generally, clusters of schools with elevated air pollution levels had also elevated access to fast food retailers. Such co-occurrence might explain dynamics of urban activity in those schools’ neighbourhoods and might indicate the contribution of fast food retailers’ emissions to air pollution at neighbourhood scale (Robinson et al., 2018; Shah et al., 2020; Vert et al., 2016). Our estimated exposure to greenspace surrounding schools was highly right-skewed, implying that most London schools had comparable access to public greenspace, except 20% of schools (equivalent to 558) that had more than 10 ha area of green space available in their neighbourhood. With respect to road safety around the schools, 481 schools (~16%) were characterized as high risk with on average more than four child pedestrian crashes in 3 years.

Our study confirms patterns of exposure disparities among London schools. Schools with high levels of air pollution, surrounded by many fast food retailers, and high number of child pedestrian crashes were located in the most deprived areas, all of which make it challenging for the health gap to close. The only exception was one cluster (cluster 10) in the affluent central London neighbourhood, where both air pollution and the number of fast food retailers were high, but the level of deprivation was low. Child pedestrian crashes were considerably higher around schools located in areas with higher deprivation (e.g., clusters 2,8, and 11). One potential reason can be that children in deprived area tend to rely more on walking or cycling to and from school, increasing their exposure to risk of road traffic accidents (Sonkin et al., 2006). Additionally, child pedestrian crashes were concentrated around schools located in areas with higher percentage of population from Black, Asian, and minority ethnic groups. Further research to fully understand road and environmental risk factors that derives such disparities is required.

Our study framework has been developed such that we can interpret exposure profiles at various levels of granularity (e.g., school, subgroup of schools, subset of LSOAs, Local Authorities). At the lowest level of granularity, schools can use our results to compare themselves, recognize their priorities and work toward them. For example, schools can participate in School Street policies where motorized traffic is restricted for 30–60 min at the school gates at the start and end of the school day. Such policy reduces traffic flow in school neighbourhoods during drop-off and pick-up hours address, addressing both air quality and traffic safety around schools. Alternative school-based actions to improve air quality and road safety include installing green barriers, dedicating drop-off zones with restricted stay time to decrease idling times, educational campaigns for pupils and parents, providing active travel amenities (e.g., secure bike storage), and developing organised walking/biking/scooting buses supervised by adults along a pre-specified route (Shoari et al., 2021b). Around 16% of London schools do not have any public park and garden within 400 m of their neighbourhoods. If schools do not have resources to compensate for the lack of access to greenspace through school grounds, there is a need to create opportunities outside schools through the shared use of outdoor space with other schools, and trips to nature. When an unhealthy food environment around schools is a major concern, improving the quality of school meals can encourage pupils to take school meals, which provide healthier food and drink options compared to fast food retailers (Hart, 2016). Consulting with pupils on the food preferences, including healthy options in vending machines, combined with closed-gate policies at school lunchtime, educational training programs on the importance of a balanced diet can increase the likelihood of uptake of healthier food options.

At the highest level of granularity, our study can serve local authorities and policymakers to assess the needs and amenities in a given area and work with schools to develop school-based interventions and complement those with other corrective measures. An example of such approach to improve air quality is the Ultra Low Emission Zone policy in London, which bans highly polluting vehicle entering a restricted zone. As a result of this policy, the concentration of NO_2 in 96% of primary schools in Central London has been reduced to below 40 μg/m^3. Expansion of this policy would broaden the benefits by improving air quality around polluted schools that were identified by our study. In terms of strategies to deal with unhealthy eating, with 84% of total fast food retailers being located within 400 m of schools and a significant proportion of pupils (especially secondary school pupils) purchasing lunch from a nearby store, strategies to restrict easy access to unhealthy food need to be integrated with those that improve pupils eating habits. Some potential options include bans on the opening of new fast food retailers in the proximity of schools, limits on the proximity of fast food retailers to schools, incentive for retailers that provide healthy food option, and providing vouchers to encourage purchase of healthier food and drink options especially in the most deprived areas. With respect to road safety, deprivation showed to be a determinant factor. Implementing targeted intervention in hotspots of crashes becomes of paramount importance, especially when active travel for school journeys continues to be a core strategy to increase physical activity, and reduce traffic flow, congestion, and road risk. Some key actions include considering traffic calming measures, school 20 mph zones, and engineering adequate infrastructures that allow pupils have a safe walking or cycling experience. To ensure adequate access to greenspace, there is need for a collaborative response from local authorities, Department for Education, and urban planners to safeguard school grounds, to invest in creating new greenspace in schools, and to improve the quality of existing public parks and gardens around schools.

Our study is different from previous investigations on school exposures in several ways. First, we considered simultaneous exposure to multiple urban features surrounding schools, rather than including a single feature that is typically applied. Therefore, our results allow an integrative approach to decision-making, accounting for multiple exposures and considering synergic or conflicting effects of an intervention. For example, when a cluster of schools face simultaneously high exposure to air pollution, poor food environment, and unsafe roads (such as cluster 5 and 9), interventions to promote active travel to school that aim to reduce air pollution and increase physical activity, need to be combined with interventions to make the commute roads safer for children. Extending this work and linking the exposure profile to a health outcome would help us understand which combination of exposures is more detrimental to health, which in turn is useful for prioritising policies that target schools most negatively affected. Second, the adopted methodology allows for flexibility in modelling in the sense that it can accommodate correlated data, multimodal distributions, as well as outliers without compromising the inference. Third, our approach relies on a non-parametric approach where the number of parameters is not fixed and can vary according to data complexity, therefore, the analyst does not need to the number of clusters in advance.

A possible extension to the current model could be evaluating how different clusters are associated with various health outcomes. However, we could not elucidate this question in our study because we lacked school-level health data for all schools in London. Including health outcomes in the analysis could shift how schools' neighbourhoods cluster together and could allow us to make inferences on how exposure profiles can imply health-promoting and health-damaging clusters of schools. Due to data availability issues, we only considered five urban environment features. Once data on other urban environment features becomes available, we can adapt our study framework to incorporate new features such as noise pollution, crime, advertising for unhealthy food (Herrera and Pasch, 2018) and tobacco (Handayani et al., 2021), among others. Another limitation is that we used 2013 air pollution data. Additionally, we did not have data on other confounding variables for all London schools. We acknowledge that data representing urban features have been collected in different years, but the urban features used in this study were considered to be stable over a relatively short time period.

Our results can be used to link multiple exposures in school neighbourhoods to a physical and/or mental health outcome. Furthermore, our study can be used as a basis to evaluate the impact of public health policies and interventions on the change on exposure levels in school-aged children. We provided a tool to help schools, public health officials, "school superzone" officials, local authorities, and policy-makers to understand schools exposure to specific features of urban environment, identify the subgroups of schools with similar exposure patterns, and to uncover which urban feature(s) is the dominant exposure in each subgroup. For example, if the focus of a public health policy is on improving access to greenspace for children, our results can be used to identify school neighbourhoods with similar exposure patterns, with priority to be given to those with less access to greenspace. This tool improves our understanding of complex exposure patterns of schools, which is essential to design effective public health measures targeted to vulnerable schools, and to evaluate the effect of intervention or policies that aim to make schools' environments healthier.

Uncited references

CRediT authorship contribution statement

Niloofar Shoari: Conceptualization, Methodology, Formal analysis, Funding acquisition,Writing - original draft, Writing - review & editing. **Sean Beevers:** Data curation. **Michael Brauer:** Conceptualization, Writing - original draft, Writing - review &

editing. **Marta Blangiardo:** Conceptualization, Methodology, 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

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