Environmental Research 231 (2023) 116087

Contents lists available at ScienceDirect

Environmental Research

journal homepage: www.elsevier.com/locate/envres

Joint associations and pathways from greenspace, traffic-related air pollution, and noise to poor self-rated general health: A population-based study in Sofia, Bulgaria

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ARTICLE INFO

Handling Editor: Jose L Domingo

Keywords:
Garden
Greenness
Mediation
Physical activity
Traffic noise
Tree cover

ABSTRACT

Background: Little is still known of how multiple urban exposures interact as health determinants. This study investigated various ways in which greenspace, traffic-related air pollution, and noise could operate together, influencing general health status.

Methods: In 2022, a cross-sectional population-based survey was conducted in Sofia, Bulgaria. Included were 917 long-term adult residents who completed questionnaires on poor self-rated health (PSRH), total time spent in physical activity (PA), home garden presence, time spent in urban greenspace and nature, and sociodemographics. Residential greenspace was operationalized using the normalized difference vegetation index (NDVI), tree cover density, number of trees, and access to local greenspace and parks. Nitrogen dioxide (NO_2) was modeled for the study area. Road traffic, railway, and aircraft day-evening-night sound levels (L_{den}) were extracted from EU noise maps. Area-level income and urbanicity were considered. Analyses included multivariate ordinal regressions, interactions, and structural equation modeling (SEM).

Results: Associations with PSRH were per 0.10 NDVI $_{300\ m}$: OR = 0.65 (0.42–1.01), home garden: OR = 0.72 (0.49–1.07), per 5 μg/m^3 NO_2: OR = 1.57 (1.00–2.48), per 5 dB(A) L_{den} road traffic: OR = 1.06 (0.91–1.23), railway: OR = 1.11 (1.03–1.20), and aircraft: OR = 1.22 (1.11–1.34). Spending >30 min/week in nature related to better health. In multi-exposure models, only associations with aircraft and railway L_{den} persisted. People with lower education and financial difficulties or living in poorer districts experienced some exposures stronger. In SEM, time spent in nature and PA mediated the effect of greenspace.

Conclusions: Greenspace was associated with better general health, with time spent in nature and PA emerging as intermediate pathways. NO_2, railway, and aircraft noise were associated with poorer general health. These results could inform decision-makers, urban planners, and civil society organizations facing urban development problems. Mitigation and abatement policies and measures should target socioeconomically disadvantaged citizens.

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https://doi.org/10.1016/j.envres.2023.116087
Received 25 February 2023; Received in revised form 4 May 2023; Accepted 8 May 2023
Available online 9 May 2023

1. Introduction

Many scientific papers on urban exposures and health begin by reminding readers of the growing urbanization trend worldwide, and for a good reason. Research evidence now suggests that reducing harmful urban exposures, such as air pollution and noise, and promoting salutogenic ones like greenspace, is instrumental for addressing burden of disease (Nieuwenhuijsen, 2021) and could prevent up to 20% of premature deaths in some cities (Mueller et al., 2017, 2021). The call for compact urban development widely addressed in the New Urban Agenda (United Nations Human Settlements Programme, 2017) and the related densification may provide better public transportation accessibility and proximity to most urban environments, including greenspace (United Nations Human Settlements Programme, 2013). However, when compactness and density are coupled with high motorization rate, congested and unfriendly streets, the benefits from such urban development can shrink (Schindler and Caruso, 2014). To maximize population health benefits, efforts for designing healthier and livable cities should be supported by an understanding of the ways in which these exposures intertwine and work together (Rugel and Brauer, 2020; Mueller et al., 2021; Tonne et al., 2021).

One of the valuable salutogenic resources of cities is green infrastructure. Greenspace exposure is an umbrella term that captures the presence or proximity of green residential infrastructure (e.g., parks, street trees), as well as accidental or deliberate interaction, be it viewing from afar or actually spending time in, vegetation-dominated landscapes (Markevych et al., 2017; Teylor and Hochuli, 2017). People residing in greener neighborhoods and engaging in nature-based activities tend to suffer from noncommunicable diseases less often (Twohig-Bennett and Jones, 2018; Yang et al., 2021), recover faster from disease states (Barton et al., 2016; Jimenez et al., 2021), and in general seem to live happier (Astell-Burt et al., 2022) and longer lives (Vienneau et al., 2017; Rojas-Rueda et al., 2019). A health impact assessment across almost 1000 European cities recently revealed that 43 000 annual deaths could be prevented (Barboza et al., 2021) if the WHO recommendation on access to urban greenspace within 300 m of every home was met (World Health Organization, 2016). Similar observations across multiple studies from various disciplines are supported by long-held beliefs that green settings can quickly reduce psychological and physiological stress (Ulrich, 1979, 1981, 1983), and enable the recovery of attentional (Kaplan and Kaplan, 1989; Kaplan, 1995) and other coping resources needed to resist daily hassles and demands that threaten health and well-being (Hartig, 2021). Greener neighborhoods can also foster health-enhancing behaviors such as active commuting or other more structured forms of physical activity (Markevych et al., 2017). In turn, physical activity is one of the key pathways linking greenspace to better health (Markevych et al., 2017; Dzhambov et al., 2020). It activates various metabolic, neurobiological, and psychosocial processes leading to weight-reduction, cardiometabolic and musculoskeletal fitness, better sleep, self-esteem, mental health, and cognitive performance, and reduced mortality (Warburton et al., 2006).

In addition, green infrastructure may offset the harmful effects of traffic-related air pollution (TRAP) and noise in cities by physically reducing them (Nowak et al., 2006; Van Renterghem et al., 2015), by mitigating annoyance (Van Renterghem, 2019; Schäffer et al., 2020), or by simply competing for space with their sources (Haaland & Konijnendijk van den Bosch, 2015; Tappert et al., 2018). As counterparts to greenspace, TRAP and traffic noise hold prominent places as environmental risk factors for ill-health (World Health Organization, 2018; World Health Organization, 2021). Air pollution is globally the 4th most important risk factor for premature mortality (Health Effects Institute, 2020). Direct toxicity of air pollutants and their capacity to induce oxidative stress and systematic inflammation in the body underlie multiple adverse health outcomes linked to residential air pollution, such as respiratory, cardiovascular, neurological, and mental health diseases, just to name a few (Thurston et al., 2017; HEI Panel, 2022). TRAP is often accompanied by high levels of noise, which acts as a stressor causing sympathetic activation, endocrine and immune system dysregulation, and ultimately leads to vascular dysfunction, where tissue damage is mediated by stress hormones, oxidative stress, and pro-inflammatory mediators (Münzel et al., 2018, 2020, 2021; Hahad et al., 2022). According to a series of WHO reviews and other literature, traffic noise is responsible for adverse outcomes like noise annoyance, diminished mental well-being, sleep disturbance, cardiometabolic diseases (World Health Organization, 2018; Hegewald et al., 2020; van Kamp et al., 2020; Gui et al., 2022), and cardiovascular mortality (Cai et al., 2021). However, in spite of its recognition as an environmental risk factor, traffic noise, especially from sources other than road traffic, is rarely investigated as an intermediary between greenspace and health, unlike air pollution (Dzhambov et al., 2020).

It therefore stands to reason that mechanistic studies including all three exposures could provide valuable insights for disease prevention. However, we still know relatively little of how greenspace, air pollution, and noise operate together (Rugel and Brauer, 2020), specifically in combination with behavioral health determinants like physical activity. It is conceivable that while greenspace is conducive to physical activity (Markevych et al., 2017), air- and noise-polluted neighborhoods may discourage people from spending time outdoors, commute, and exercise (Dzhambov et al., 2018b, 2018c). Exploration of the pathway to health through physical activity is becoming exceedingly common in greenspace and health research (Dzhambov et al., 2020), but only a handful of studies on air pollution and noise have formally investigated it (Dzhambov et al., 2018c; Wang et al., 2019; Hautekiet et al., 2022). Fewer still have considered greenspace, air pollution, and noise jointly, let alone have attempted to disentangle their interrelationships (cf. Rugel and Brauer, 2020). For example, Klompmaker et al. (2019) analyzed whether greenspace, air pollution, and traffic noise confounded, modified, and/or mediated (i.e., served as intermediary variables) each other's effects on poor self-rated general health. The authors concluded that evaluating only one of multiple correlated exposures biased effect estimates from single-exposure models. Such efforts to move the field forward remain isolated though. Furthermore, focusing predominantly on road traffic noise, as either co-exposure or mediator, fails to account for the fact that differences in exposure patterns, temporal, and spectral characteristic of different noise sources can produce quite different physiological reactions (World Health Organization, 2018; Brink et al., 2019). For instance, aircraft noise instigates a stronger annoyance response and is more harmful at the same intensity level than other traffic noise sources (World Health Organization, 2018; Brink et al., 2019). Railway noise, on the other hand, is usually accompanied by ground-borne vibration, which adds to its impact on local residents (Maclachlan et al., 2018).

We endeavored to address some of the identified gaps in the literature by investigating various ways in which greenspace, TRAP, and noise could influence general health status. We hypothesized that higher levels of greenspace and lower TRAP and traffic noise would be associated with better health. To test these assumptions, we employed multiple exposure indicators, including actual use of greenspace, and considered both individual and area-level factors. The study area chosen was the capital of Bulgaria, Sofia, which was ideally suited for testing our research hypothesis, because of its topography and infrastructure, which generate sufficient gradients and combinations of greenspace, TRAP, and traffic noise. Sofia has one of the highest air pollution-related mortality rates in the world (Health Effects Institute, 2022a) and among the heaviest burdens of disease from traffic noise in Europe (Khomenko et al., 2022). Additionally, over 70% of the population falls short of greenspace exposure targets (Barboza et al., 2021). Despite that, to date, there have been no population-based studies of the long-term effects of these exposures in the country.

2. Methods

2.1. Study design and sampling

A cross-sectional survey was conducted in Sofia, Bulgaria, in the period July 16 – December 7, 2022. To ensure sufficient exposure variation, we employed a clustered sampling scheme. Eight spatial typology classes were defined on the basis of different combinations between relatively high and low levels of greenspace, air pollution, and traffic noise (see Table S1). Criteria used to describe these typologies were as follows.

- Greenspace: presence/absence of public, urban greenspace and/or natural, recreational areas within 300 m road network distance of the residential address, presence/absence of semi-public or private greenspace within 20 m distance, or area-level normalized difference vegetation index (NDVI) value during the dry summer season above/below 0.7 within 5 m buffer (to guarantee differentiation between more abundant core vegetation and scarce young vegetation, the latter most often found at the edge of missives and/or on poor urban soils compacted by past construction works and irregular parking);
- TRAP: >/< 50 m Euclidean distance to primary roads (classes I – speed urban highway, II – urban highway, or III – district artery, or IV – major street if it is a street canyon with average aspect ratio ≥1);
- Traffic noise: >/< 70 dB(A) road, air, or rail traffic day-evening-night sound level (L_{den})
- Household air pollution: >/< 200 m Euclidean distance to ≥ 10 households registered as using fossil fuel for heating.

Data sources used for this classification were detailed cadastral and municipal land use-land cover (LULC) maps (https://sofiaplan.bg/en/index-en/), Sofia's strategic EU noise maps (https://cdr.eionet.europa.eu/bg/eu/noise/df8/2017/), an existing Sentinel-2A NDVI layer from August 2018, and information on household solid fuel appliances obtained at the address level from the National Statistical Institute's census in 2011, additionally processed by the Department of Spatial and Strategic Planning of Sofia Municipality for research purposes (https://api.sofiaplan.bg/datasets/218).

A professional survey company was contracted to carry out field interviews ensuring that the sample was random and representative of the general population. For each spatial typology class, the survey company was provided with a list of multiple randomly generated sampling clusters and addresses. Interviews were conducted by quota within nests (spatial typology class) so that the sampled units corresponded to the socio-demographic structure of the population. Georeferenced demographic data from the census in 2011 informed age-group and gender quota within each cluster, so that the sample was also representative of local populations. Adult household members (aged 18–65) whose characteristics corresponded to quota and inclusion criteria were selected. A questionnaire, drawing on items from the European Health Interview Survey 2019 (https://www.nsi.bg/en/content/3364/european-health-interview-survey), was developed and tested for clarity, length, and face validity with 50 Sofia inhabitants. Then, we trained interviewers to administer the questionnaire.

Face-to-face tablet-assisted interviews were administered at participant's home. The average duration of an interview was about 20 min. Included were non-institutionalized, competent, and fluent in Bulgarian working-age adults (18–65 years) who had lived in their present dwelling for at least five years prior to the interview. The target sample size of 1020 could not be reached in full, because out of 5731 eligible respondents, only 917 agreed to take part in the survey (16% response rate).

The study design was approved by the Ethics Commission at Sofia University "St. Kliment Ohridski" (№ 61-13-8/July 01, 2022). The study complied with established ethical principles, participants gave verbal informed consent, and their personal information was processed according to the General Data Protection Regulation in the EU.

2.2. Poor self-rated health

Poor self-rated health (PSRH) was chosen as an outcome because this construct is widely used in epidemiology as a comprehensive and robust measure of general health (Idler and Benyamini, 1997; DeSalvo et al., 2006). This single question was formulated as "*In general, how would you rate your health?*", with no specific time frame reference. Responses were given on a 5-point scale (1 = "Very good", 2 = "Good", 3 = "Satisfactory", 4 = "Poor", and 5 = "Very poor"). PSRH was used as an ordered-categorical variable.

2.3. Exposure assessment

2.3.1. Greenspace

Expert recommendations to operationalize greenspace using different indicators were followed, in order to capture different types of greenspace exposure (Markevych et al., 2017). Dimensions considered were greenspace availability, accessibility, and use, operationalized with both objective and self-reported measures. Availability was assessed via NDVI, tree cover density, number of individual trees, and having a domestic garden. Geospatial analyses were conducted with QGIS v. 3.28.2 (QGIS Development Team (2022). QGIS Geographic Information System. Open Source Geospatial Foundation Project. http://qgis.osgeo.org) and ArcMap v. 10.8.1 (ESRI, 2020. ArcGIS Desktop: Release 10.8.1 Redlands, CA: Environmental Systems Research Institute).

NDVI served as a primary exposure indicator, as it is commonly used as proxy for general level of vegetation biomass (greenness) (Markevych et al., 2017). It is calculated with the following expression: NDVI = (NIR - RED)/(NIR + RED), where NIR is near-infrared light band and RED is visible red-light band (Tucker, 1979). The possible range for NDVI is between −1 and +1, where higher values closer to +1 correspond to lush vegetation, and negative values correspond to built-up land cover and water. For these calculations, we used one could-free multispectral satellite image (spatial resolution 10 m × 10 m) taken by the Sentinel-2A sensor and downloaded from the Copernicus Open Access Hub (https://scihub.copernicus.eu/). The acquisition date for this image was July 22, 2022, which falls within the data collection period and represents the time of year with most abundant vegetation in Sofia to maximize exposure gradients. The image was preprocessed with the Semi-Automatic Classification Plugin for QGIS. Although it has been recommended to set negative NDVI pixels to zero or missing values, so as not to capture the effect of bluespace at the lower end of the NDVI scale (Markevych et al., 2017), such open water bodies were not present in our study area, so negative pixels were not recoded. Average NDVI values within Euclidean distance buffers of 50 m, 100 m, 300 m, and 1 km around each residence were calculated. The 300 m buffer was selected as the main one, in accordance with earlier studies in European context (Konijnendijk, 2022; Nieuwenhuijsen et al., 2022) and the WHO guideline on having a greenspace at ≤ 300 m linear distance (5 min' walk) from home (World Health Organization, 2016).

Tree cover density (0–100%) was averaged within these same buffers around the home address. Tree cover data for the year 2018 were obtained at a 10 m × 10 m resolution from the Copernicus service (https://land.copernicus.eu/pan-european/high-resolution-layers/forests/tree-cover-density).

The **number of trees** within each buffer was also counted. This layer was obtained from the Department of Spatial and Strategic Planning of Sofia Municipality (https://sofiaplan.bg/portfolio/trees-index/). Briefly, based on 3671 high-resolution orthographic images taken in 2020, individual trees were automatically classified using DeepForest machine learning. The classification algorithm identified tree canopies and georeferenced the approximate planting centroid of each tree. Validation comparison with a field audit of 6873 trees showed over 80%

accuracy of the classification.

Access to local greenspace and parks, taken as separate classes, within 300 m Euclidean distance from each address was determined based on LULC maps from the Department of Spatial and Strategic Planning of Sofia Municipality (https://sofiaplan.bg/api/). Local greenspace included small neighborhood green spaces and pocket parks.

Participants were asked whether their dwelling had a **garden/yard** they could use. They also reported separately the **time spent in urban green spaces** and **time spent in natural greenspace** outside the city during the last week. Potential responses were “No time at all”, “< 30 min”, “31–60 min”, “61–120 min”, “121–180 min”, “181–240 min”, and “> 240 min”.

2.3.2. Air pollution

Nitrogen dioxide (NO_2) was used as a proxy for TRAP. Mean annual NO_2 concentrations were measured in 2021 with passive diffusion tubes (Passam, Switzerland) at 27 locations (Popov and Hlebarov, 2022). These locations were adjacent to streets with intense traffic and in some cases where street canyons are formed. All measurements were made using pairs of diffusion tubes and in accordance with the requirements of ANNEX III of Directive (2008)/50/EC. Based on these data, NO_2 was modeled for the entire study area at a resolution of 20 m x 20 m using inverse-distance weighted interpolation from the primary and secondary street network from points spaced 20 m apart along street segment lines. More specifically, Weighted Ensemble L2 algorithm in AutoGluon was used to predict NO_2 from information on traffic counts, infrastructure characteristics, including road class, capacity, cover material, speed limit, slope, and space syntax integration and choice parameters, along with others. The performance of the model was evaluated using mean absolute percentage error (MAPE = 5%) and coefficient of determination ($R^2 = 0.90$).

2.3.3. Traffic noise

Road traffic, railway, and aircraft L_{den} levels were extracted from the strategic noise maps of Sofia delivered under the European Noise Directive for the year 2017 (https://cdr.eionet.europa.eu/bg/eu/noise/df8/2017/). Briefly, an acoustic engineering company had modeled traffic noise from different sources at a spatial resolution of 10 m × 10 m, at 4 m above the ground level for all receivers, using as input data on traffic characteristics, infrastructure, urban fabric, and meteorology. **Road traffic noise** was calculated according to the French national method “NMPB-Routes-96” and the standard “XPS 31–133”; for **aircraft noise,** EC AC, CEAC Doc 29 – “Report on Standard Method of Computing Noise Contours around Civil airports“, 1997 was used; and for **rail traffic noise** (including city trams), the Dutch method “Reken-en Meetvoorschrift Railverkeerslawaai’96, Ministerie Volkshuisvesting, Ruimtelijke Ordening en Milieubeheer” (RLM2ISO). All calculations were performed in LimA v. 11 (Brūel & Kjær). Short-term measurements at 76 locations and additional 23 full-day measurements from the Regional Health Inspectorate were used for calibration and validation of the model (SPECTRI, 2017).

As these noise maps were in polygon format, each residential address was assigned the 5-dB(A) band of the polygon it intersected with or that of the nearest polygon (in isolated cases of an empty space at the address point, in the road traffic noise layer). Aircraft and railway L_{den} were modeled down to a minimum of 10 dB(A). Following earlier examples (Floud et al., 2013; Kim et al., 2022), addresses outside the modeled aircraft and railway noise contours were not excluded from the analyses, rather effectively assumed to be unexposed (i.e., assigned a value of <10 dB(A)). As a sensitivity analysis, for aircraft and railway L_{den}, we set all levels <30 dB(A) to the same value, to test whether potentially low accuracy of the acoustic modeling at very low levels had affected the results. All L_{den} indicators were coded numerically and entered in the analyses as continuous variables, so that one unit increase represented a 5-dB(A) change in sound levels (cf. Floud et al., 2013). Fig. S1 shows participants’ home addresses overlaying greenspace, NO_2, and L_{den} maps.

2.4. Physical activity

Total time spent in physical activity in the last week (hours/week) was calculated as the product of reported frequency (days per week) and average duration/day of 1) walking, 2) active travel by bicycling, skateboarding, inline skating, etc. and 3) doing sports, each for at least 10 min at-a-time. Preliminary analyses revealed that a combined measure of total time spent in physical activity was related to the exposures and PSRH more strongly than the time spent in any specific type of physical activity alone.

2.5. Confounders and effect modifiers

Information on potential confounders and effect modifiers was collected via questionnaires and area-level statistics. Socio-demographic variables included age, self-reported gender, ethnicity, education, and perceived household income. Due to the small number of cases in some categories, ethnicity was dichotomized (Bulgarian vs. non-Bulgarian), and educational levels were collapsed into three groups (basic/lower, high school/vocational, and university degree). Perceived household income, which we will refer to as perceived economic struggle or financial difficulties, was measured with the question: “*Considering the total monthly income of your household, how easy is it to make ends meet?*“. Responses to this question were given on a 6-point scale (1 = “Very easy”, 2 = “Easy”, 3 = “Mostly easy”, 4 = “Somewhat difficult”, 5 = “Difficult”, 6 = “Very difficult”). In addition, aggregate information on mean income per month in each of the 24 districts of Sofia was provided for the year 2017 by the National Revenue Agency (https://sofiaplan.bg/api/). Month of data collection was also used as a confounder in some analyses. Participants were also asked how much time they spent at home per day (i.e., per 24 h-period).

As a proxy for urbanicity, we calculated the average building height in buffers of interest. We used the 2012 dataset (10 m × 10 m) from the Copernicus Open Access Hub (https://scihub.copernicus.eu/). Following preliminary tests, building height was preferred over imperviousness density since the latter was highly collinear with NDVI, and building height performed better as a confounder.

2.6. Statistical analysis

2.6.1. Descriptive analyses and bivariate tests

Of the variables used in the study, only home garden, education, and ethnicity had missing values (<2%), therefore the analytical sample for some tests is lower than 917. Following distributional tests, the patterns of association in the dataset were explored with Spearman correlations. PSRH was treated as an ordered-categorical variable, as dichotomizing it would have reduced statistical power (e.g., in stratified and categorical tests).

Most analyses were conducted in Stata/MP (StataCorp. 2021. Stata Statistical Software: Release 17. College Station, TX: StataCorp LLC), while for structural equation modeling we used the packages lavaan v. 0.6–10 and lavaan. survey v. 1.1.3.1 (Rosseel, 2012) in R v. 4.1.2. (R Core Team (2021). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.). A p-value of <0.05 was considered statistically significant, except in effect modification tests (see section 2.6.2).

2.6.1. Multivariate regression models

Associations between greenspace, NO_2, and L_{den} with PSRH were examined by fitting multivariate ordinal regressions, where odds ratio coefficients (OR) represented the likelihood of PSRH increasing by one level. In single-exposure models, PSRH was regressed on each exposure indicator one-at-a-time, while the multi-exposure models included together $NDVI_{300\ m}$, home garden, NO_2, road, railway, and aircraft L_{den}.

Two models with an incremental adjustment for confounders were rendered. Model 1 controlled for individual-level confounders (age, gender, ethnicity, education, and economic struggle), and Model 2 was additionally adjusted for area-level income and urbanicity. No multicollinearity was detected (variance inflation factor <5, Tolerance >0.2). To account for the complex sampling scheme, standard errors were adjusted for 95 clusters.

2.6.2. Sensitivity analyses

Fully-adjusted multivariate models were rendered without an adjustment for clustering to determine whether that would affect conclusions. In another sensitivity analysis, single-exposure associations of $NDVI_{300\ m}$, home garden, NO_2, road traffic, railway, and aircraft L_{den} with PSRH were stratified by potential effect modifiers and the significance of between-subgroup differences was tested at a relaxed $p < 0.1$ level (Selvin, 1996; Greenland and Rothman, 1998; Marshall, 2007). When tested as modifiers, some variables were recoded as follows to increase power for these tests: age was categorized as ≤ 35 yrs, 36–55 yrs, and >55 yrs; perceived economic struggle was split at the median; area-level income, at 1446 BGN; duration of residence, at 20 years; time spent at home, at 12 h/day; railway and aircraft L_{den}, at 30 dB(A); road traffic L_{den}, at 60 dB(A); and NO_2, at 37 μg/m^3. To check for additive interaction (Andersson et al., 2005), we planned to calculate relative excess risk due to interaction (RERI) between exposures, for which we had found both main and interaction effects on PSRH. Finally, we rerun the main models (Model 2 adjustments) with all aircraft and railway L_{den} levels <30 dB(A) set at the same value.

2.6.3. Structural equation modeling

As a recommended analytical technique for disentangling underlying mechanisms (Dzhambov et al., 2020), structural equation modeling (SEM) was used to test the adequacy of the conceptual model presented in Fig. 1. That is, $NDVI_{300\ m}$, home garden, NO_2, and L_{den} were assumed to directly lead to PSRH. $NDVI_{300\ m}$/garden could also have indirect associations with lower PSRH through lower NO_2, L_{den}, more time spent in greenspace, and higher physical activity. NO_2 and L_{den} could indirectly relate to PSRH through lower physical activity.

The model was specified with $NDVI_{300\ m}$ as an indicator of residential greenspace for both conceptual reasons (see section 2.3.1 on the 300 m buffer) and because this indicator was the most strongly associated with PSRH in the multivariate models described in section 2.6.1. A priory covariances were assumed between NO_2 and road traffic L_{den}. However, in the course of model refinement informed by inspection of modification indices, additional model-implied covariances were added. Besides the core variables, the model included paths involving gender, age, ethnicity, perceived economic struggle, area-level income, urbanicity, and month of year. Since many of the endogenous variables were ordered categorical or binary in nature, we used the diagonally weighted least squares (DWLS) estimator (DiStefano and Morgan, 2014), which estimates a polychoric correlation matrix. To achieve uniformity of variable scales and because we were mostly interested in direction and size of regression coefficients, all variables were standardized. Indirect effects were computed as the product of the regression coefficients associated with their constituent paths. Standard errors and confidence intervals for all regression coefficients were constructed via bootstrapping (5000 draws), which is considered superior to other methods for indirect effects indifference (Hayes, 2013). However, a model would not converge if both bootstrapping and clustered standard errors were requested, therefore, we also report results of an alternative model that used clustered standard errors together with robust maximum likelihood estimation with a mean- and variance adjusted test statistic (MLMVS). Since DWLS and MLMVS models led to the same conclusions and the DWLS performed better in terms of variance explained in endogenous variables, the DWLS results were prioritized. Coefficients from this model for categorical endogenous variables were probit regression estimates (i.e., changes in units of standard deviation for the transformed outcome variable, where the probit model transforms probabilities into z-scores from a standard normal distribution).

Goodness of model fit was determined with the help of commonly used fit indices according to the following recommended cut-offs (Hu and Bentler, 1999): non-significant χ^2 ($p > 0.05$); comparative fit index (CFI) ≥ 0.95; root mean square error of approximation (RMSEA) ≤ 0.06 with a 90% CI ≤ 0.06; and standardized root mean squared residual (SRMSR) ≤0.08. We also report the parsimony normed fit index (PNFI), which accounts for model complexity and was expected to be > 0.50 (Iacobucci, 2010). These cut-offs may be somewhat low when a DWLS

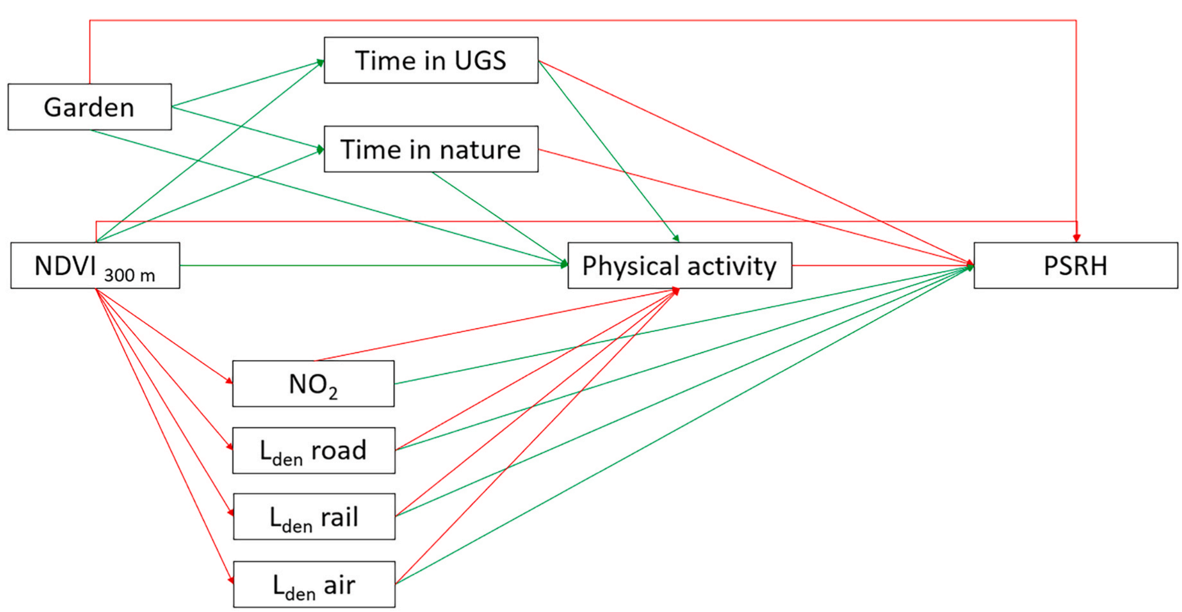

Fig. 1. Conceptual path diagram of the hypothesized associations between greenspace, traffic-related air pollution, and noise with poor self-rated health. Abbreviations: L_{den} – day-evening-night sound level; NDVI – normalized difference vegetation index; NO_2 – nitrogen dioxide, PSRH - poor self-rated health, UGS – urban greenspace. Poor self-rated health is an ordered categorical variable, where higher values indicate worse general health status. Legend: Green paths indicate associations with a positive sign (an increase), and red arrows, associations with a negative sign (a decrease).

estimator is used (Xia and Yang, 2019), but good model fit was also supported with the MLMVS estimator, for evaluating which we used robust alternatives of these test statistics with the same cut-offs. Modification indices were used to improve model fit by addressing localized areas of ill-fit (Brown, 2015). In some cases, we refer to the observed associations/paths in the SEM as “effects” in line with standard terminology in the literature, but we attach no formal claims of causality to that term.

3. Results

3.1. General description of the sample and associations

Tables 1 and 2 and Fig. S2 show participant’s characteristics as well as distributions of environmental exposures. The sample comprised 917 adult residents of Sofia. A little more than a half of participants was female. Participants’ age ranged from 18 to 65 years. Half of participants had a university degree and the majority considered themselves ethnic Bulgarians. Most participants were long-term residents of their area. The majority reported “very good” or “good” general health. Comparison of this sample’s characteristics with the general population of Sofia in this age range is shown in Table S2. Overall, our sample had slightly more ethnic Bulgarians and university graduates, more people reporting “Satisfactory health” and fewer reporting “Very good health”, less middle-aged and more 60–65-year-olds. Greenspace indicators, NO_2 and L_{den} variables varied from relatively low to moderately high levels (Fig. S2).

Table 1
Study population characteristics (N = 917)[a].

Characteristics	
Socio-demographics	
Age [years] (mean, SD)	44.51 (14.37)
Gender [male] (n, %)	425 (46.3)
Ethnicity [Bulgarian] (n, %)	866 (94.5)
Education (n, %)	
Basic or lower	50 (5.5)
High school or vocational	395 (43.1)
University degree	466 (50.8)
Economic struggle [1–6 scale] (mean, SD)	3.44 (1.04)
Very easy (n, %)	20 (2.1)
Easy (n, %)	146 (15.9)
Mostly easy (n, %)	309 (33.7)
Somewhat difficult (n, %)	323 (35.2)
Difficult (n, %)	92 (10.0)
Very difficult (n, %)	27 (2.9)
Duration of residence [years] (median, IQR)	21.00 (23.00)
Time spent at home/day [> 12 h] (n, %)	423 (46.1)
Health status	
Poor self-rated health [1–5 scale] (median, IQR)	2.00 (2.00)
Very good health (n, %)	258 (28.1)
Good health (n, %)	416 (45.4)
Satisfactory health (n, %)	213 (23.2)
Poor health (n, %)	26 (2.8)
Very poor health (n, %)	4 (0.4)
Health-enhancing activities	
Physical activity [hours/week] (median, IQR)	4.67 (5.50)
Time in urban greenspace [min/week] (n, %)	
No time at all	109 (11.9)
<30	68 (7.4)
31–60	127 (13.8)
61–120	188 (20.5)
121–180	165 (18.0)
181–240	70 (7.6)
>240	190 (20.7)
Time in nature [min/week] (n, %)	
No time at all	529 (57.7)
<30	34 (3.7)
31–60	48 (5.2)
61–120	70 (7.6)
121–180	41 (4.5)
181–240	42 (4.6)
>240	153 (16.7)

[a] Some categorical variables contain missing data, therefore valid percentages are reported. Poor self-rated health is an ordered categorical variable, where higher values indicate worse general health status.

Table 2
Distributions of geographic variables (N = 917).

Spatial exposures	
$NDVI_{300\ m}$ (mean, SD)	0.25 (0.05)
$Trees_{300\ m}$ [count] (mean, SD)	791.30 (193.28)
Tree cover density $_{300\ m}$ [%] (median, IQR)	6.69 (7.00)
Access to local green space within 300 m (n, %)	504 (55.0)
Access to urban park present within 300 m (n, %)	172 (18.8)
NO_2 [μg/m^3] (mean, SD)	37.33 (2.24)
L_{den} road [dB(A)] (n, %)	
45–50	13 (1.4)
50–55	98 (10.7)
55–60	264 (28.8)
60–65	339 (37.0)
65–70	116 (12.6)
70–75	65 (7.1)
75–80	22 (2.4)
L_{den} rail [dB(A)] (n, %)	
<10 (unexposed)	211 (23.0)
10–15	26 (2.8)
15–20	74 (8.1)
20–25	106 (11.6)
25–30	158 (17.2)
30–35	120 (13.1)
35–40	91 (9.9)
40–45	58 (6.3)
45–50	33 (3.6)
50–55	16 (1.7)
55–60	12 (1.3)
60–65	12 (1.3)
L_{den} air [dB(A)] (n, %)	
<10 (unexposed)	214 (23.3)
10–15	125 (13.6)
15–20	80 (8.7)
20–25	134 (14.6)
25–30	143 (15.6)
30–35	98 (10.7)
30–40	44 (4.8)
40–45	78 (8.5)
45–50	1 (0.1)
Area-level income [mean BGN/month] (median, IQR)	1446.00 (499.00)
$Urbanicity_{300\ m}$ [budling height, meters] (median, IQR)	13.66 (3.97)

Abbreviations: BGN – Bulgarian lev (currency); L_{den} – day–evening–night sound level; NDVI – normalized difference vegetation index; NO_2 – nitrogen dioxide.

Bivariate correlations between the key variables in the study are presented in Table S3. PSRH was associated with older age, economic struggle, less time spent in greenspace and less physical activity, and with higher railway and aircraft L_{den}. Other correlations with environmental variables were in line with theory. NDVI and tree indicators were inversely correlated with NO_2, L_{den}, and urbanicity. A few unusual patterns can be explained by the fact that more affluent districts of Sofia tend to be in the inner parts of the city, where traffic levels and soil sealing are higher. Local green spaces in Sofia are relatively small and mostly found in the central districts, therefore their presence was inversely related to NDVI and tree indicators, while the opposite trend was observed with presence of larger public parks. In addition, people with higher education and less financial difficulties lived in neighborhoods with more trees, but also with higher NO_2 exposure and less home gardens. Likewise, area-level income was inversely related to NDVI, but positively with NO_2. (Since some of these correlation coefficients were small albeit significant, consult Table S3 for their magnitude.)

3.2. Multivariate associations between exposures and poor self-rated health

Results of multivariate models are shown in Table 3 (Table S4 provides extended results with greenspace indicators in alternative buffers).

Table 3
Associations between greenspace, traffic-related air pollution, and noise with poor self-rated health.

Single-exposure models (N = 910)	Model 1	Model 2
	OR (95% CI)	OR (95% CI)
NDVI $_{300\ m}$	**0.63 (0.43, 0.94)***	*0.65 (0.42, 1.01)*
Tree count $_{300\ m}$	0.99 (0.98, 1.00)	0.99 (0.98, 1.01)
Tree cover density $_{300\ m}$	0.89 (0.65, 1.21)	0.91 (0.68, 1.22)
Local greenspace in 300 m	1.35 (0.90, 2.06)	1.31 (0.85, 2.01)
Park in 300 m	0.97 (0.53, 1.77)	0.95 (0.52, 1.71)
Home garden (N = 898)	*0.70 (0.49, 1.01)*	0.72 (0.49, 1.07)
Time in urban greenspace/week		
0 min	1.00	1.00
<30 min	0.65 (0.37, 1.13)	0.67 (0.38, 1.18)
31–60 min	**0.61 (0.38, 0.96)***	*0.63 (0.39, 1.00)*
61–120 min	0.78 (0.49, 1.26)	0.80 (0.49, 1.28)
121–180 min	1.20 (0.69, 2.08)	1.20 (0.69, 2.10)
181–240 min	1.06 (0.51, 2.19)	1.04 (0.51, 2.13)
>240 min	0.90 (0.54, 1.52)	0.91 (0.54, 1.54)
Time in nature/wee		
0 min	1.00	1.00
<30 min	0.75 (0.39, 1.45)	0.79 (0.40, 1.56)
31–60 min	**0.52 (0.28, 0.96)***	0.54 (0.29, 1.03)
61–120 min	**0.51 (0.33, 0.79)***	**0.52 (0.33, 0.82)***
121–180 min	**0.36 (0.19, 0.67)***	**0.37 (0.19, 0.69)***
181–240 min	**0.32 (0.16, 0.67)***	**0.33 (0.17, 0.65)***
>240 min	**0.39 (0.25, 0.61)***	**0.37 (0.23, 0.61)***
NO_2	**1.56 (1.09, 2.23)***	*1.57 (1.00, 2.48)*
L_{den} road	1.06 (0.91, 1.23)	1.06 (0.91, 1.23)
L_{den} rail	**1.12 (1.04, 1.20)***	**1.11 (1.03, 1.20)***
L_{den} air	**1.18 (1.09, 1.29)***	**1.22 (1.11, 1.34)***
Multi-exposure model (N = 898)		
NDVI $_{300m}$	0.82 (0.50, 1.33)	0.87 (0.50, 1.51)
Home garden	0.86 (0.58, 1.27)	0.77 (0.52, 1.16)
NO_2	1.08 (0.74, 1.57)	1.01 (0.66, 1.54)
L_{den} road	1.04 (0.90, 1.19)	1.02 (0.89, 1.17)
L_{den} rail	**1.07 (1.00, 1.14)***	*1.07 (1.00, 1.14)*
L_{den} air	**1.13 (1.03, 1.25)***	**1.18 (1.06, 1.31)***

Abbreviations: L_{den} – day-evening-night sound level; NDVI – normalized difference vegetation index; NO_2 – nitrogen dioxide. Poor self-rated health is an ordered categorical variable, where higher values indicate worse general health status. Coefficients reported are odds ratios (OR) with their 95% confidence interval (95% CI) from ordinal logistic regression models with standard errors adjusted for clustered sampling. *Coefficient in statistically significant at $p < 0.05$. Estimates are scaled per one unit increase in the exposures as follows: NDVI – per 0.10; Tree count – per 10 trees in the 50 m, 100 m, 300 m buffers and per 100 trees in the 1 km buffer; Tree cover density – per 10%; L_{den} – per 5 dB(A); NO_2 – per 5 μg/m^3. Model 1 is adjusted for age, gender, ethnicity (Bulgarian vs. other), education, and economic struggle. Model 2 is additionally adjusted for area-level income and urbanicity (average building height in the respective buffer). In addition, in the multi-exposure models, the exposures are mutually-adjusted.

In single-exposure models adjusted for individual-level confounders, higher NDVI $_{300\ m}$ was associated with lower odds of PSRH. Similar trends were seen with tree count and tree cover density, though those estimates remained non-significant. The coefficient for home garden was borderline significant and in the same direction as for NDVI $_{300\ m}$. Spending more time in nature was the form of greenspace exposure most consistently and strongly associated with lower likelihood of PSRH. On the other hand, the odds of PSRH were higher when NO_2, railway and aircraft L_{den} levels were higher.

In the fully-adjusted models including area-level income and urbanicity, the magnitude of all observed associations remained materially unchanged. However, some previously significant estimates barely failed to reach significance. In the multi-exposure model, all associations but those with aircraft and railway L_{den} disappeared.

3.3. Sensitivity analyses

Without an adjustment for clustering in the fully-adjusted models (Model 2), some of the previously borderline estimates reached statistical significance, namely, those for NDVI $_{300\ m}$ and NDVI $_{1\ km}$, tree count $_{50\ m}$, local greenspace presence in 300 m, home garden (in single-exposure models), and railway L_{den} (in the multi-exposure model) (see Table S4).

According to effect modification tests, the presence of a home garden was more strongly related to lower PSRH in participants with lower education, more financial difficulties, and spending more than 12 h/day at home (see Table S5). The association of NO_2 with PSRH was not modified by other variables, but was significant only in females, those with high school/vocational education, those with financial difficulties, as well as in people spending no more than 12 h/day at home, and in those exposed to high levels of road traffic L_{den}. The odds associated with road traffic L_{den} were higher when participant's education was lower and in those having a garden at home. Lower education and higher road traffic L_{den} were associated with higher odds of PSRH from aircraft L_{den}. Tests for deviation from additivity were not performed, since there weren't exposures that had both main and interaction effects on PSRH.

In a final sensitivity analysis with railway and aircraft L_{den} values < 30 dB(A) merged, the odds of PSRH in Model 2 were actually increased: OR = 1.19 (95% CI: 1.06, 1.35) per 5 dB(A) railway L_{den} and OR = 1.39 (95% CI: 1.16, 1.67) per 5 dB(A) aircraft L_{den}.

3.4. Structural equation model

The DWLS SEM converged normally in 60 iterations and fitted the data reasonably well: $\chi^2_{(57)} = 126.56$, $p < 0.001$; CFI = 0.98, RMSEA = 0.04 (90% CI: 0.03, 0.05), SRMR = 0.03, PNFI = 0.40. The core paths of interest are shown in Fig. 2 (Fig. S3 shows the full path diagram). The model explained 43% of the variance in PSRH, with higher railway and aircraft L_{den}, more time spent in urban greenspace but less time in nature, lower physical activity, older age, more economic struggle, and higher area-level income leading to higher PSRH. Time spent in urban greenspace and time spent in nature were explained at 9% and 12%, respectively, and physical activity, at 29%. NDVI $_{300\ m}$ and presence of a home garden related to more time spent in nature. Having a home garden and more time spent in urban greenspace and in nature were associated with higher physical activity.

Indirect effects in this model are reported in Table 4. Higher NDVI $_{300\ m}$ related to lower PSRH through lower aircraft L_{den} and more time spent in nature. In addition, a serial mediation sequence involved NDVI $_{300\ m}$ leading to more time spent in nature, then in turn to more physical activity, and then to lower PSRH. Home gardens were associated with more time in nature and physical activity and then with lower PSRH. The total indirect effects from NDVI $_{300\ m}$ and home garden on PSRH were significant. The total effects of railway and aircraft L_{den} were also significant.

With the alternative MLMVS estimator and clustered standard errors, the model converged in 287 iterations and had similar fit statistics: $\chi^2_{(21.935)} = 23.38$, $p = 0.377$; CFI = 0.98, RMSEA = 0.01 (90% CI: 0.00, 0.02), SRMR = 0.03, PNFI = 0.40. In this model, most of the direct effects on PSRH were confirmed (see Fig. S4). However, only the path starting from home garden and operating via more time spent in nature, the total indirect effect of home garden, and the total effect of aircraft L_{den} were significant.

4. Discussion

4.1. General findings

This study investigated the associations of PSRH with greenspace, NO_2, and traffic noise in the capital of Bulgaria, Sofia. Results indicated that exposure to higher levels of residential greenspace led to better general health, while NO_2 and railway and aircraft noise were associated with worse general health. However, when all exposures were included in the same model, only the associations of aircraft and railway L_{den} with

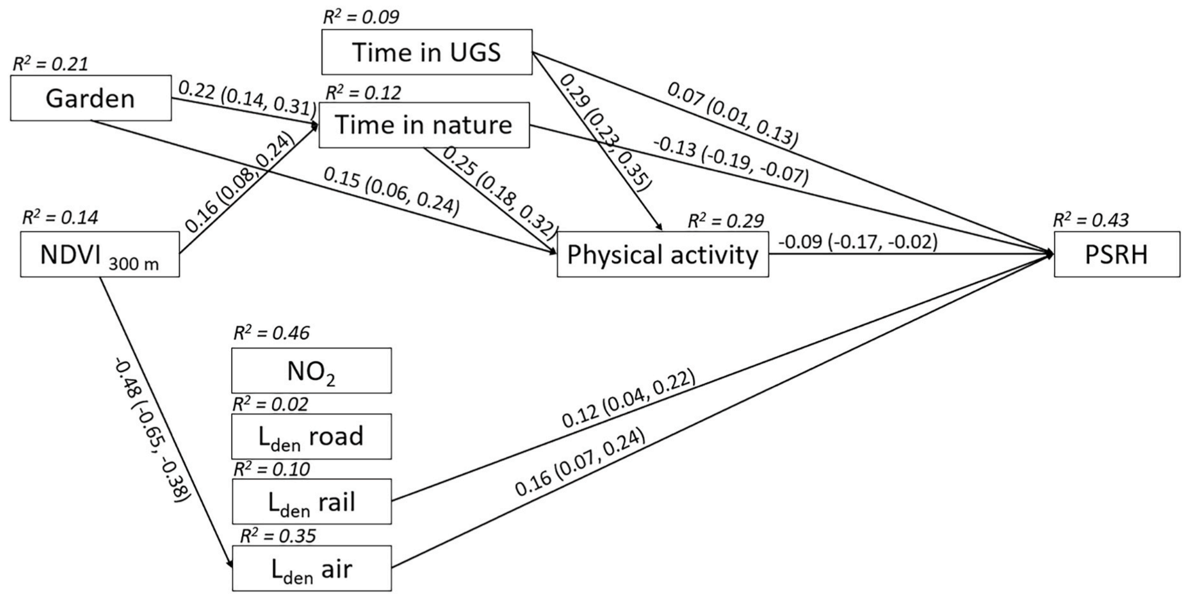

Fig. 2. Structural equation model showing estimated paths linking greenspace, traffic-related air pollution, and noise to time spent in greenspace, physical activity, and poor self-rated health (N = 904). Notes: Statistically significant standardized regression estimates are shown. Confidence intervals are constructed via bootstrapping (5000 draws). Control variables (gender, age, ethnicity, perceived economic struggle, area-level income, urbanicity, and month), covariances, and errors terms are not displayed to enhance readability. Abbreviations: L_{den} – day–evening–night sound level; NDVI – normalized difference vegetation index; NO_2 – nitrogen dioxide; R^2 – variance explained in endogenous variables; PSRH – poor self-rated health, UGS – urban greenspace. Poor self-rated health is an ordered categorical variable, where higher values indicate worse general health status.

PSRH persisted.

Greenspace in a 300 m residential buffer was related to better general health and this observation was consistent across different models, albeit borderline significant in some cases. Several studies have focused on the same outcome (e.g., Triguero-Mas et al., 2015; Dadvand et al., 2016; Astell-Burt and Feng, 2019; Klompmaker et al., 2019; Huang et al., 2022). In a recent study of multiple exposures, Klompmaker et al. (2019) reported 9% lower odds of (dichotomized) PSRH per interquartile range increase in NDVI and greenspace land-use in a 300 m buffer. In Australia, Astell-Burt and Feng (2019) observed beneficial effects on general health of tree-dominated greenspace, but not of low-lying vegetation. To discriminate between the contribution of different types and forms of greenspace in our study, we also considered associations with tree count/cover, access to local greenspace and large parks, and presence of a home garden. With some tree-based indicators and home garden, associations mostly went in the same direction as with NDVI, but were weaker in the main models. On the other hand, actual interaction with greenspace was not covered in those previous studies relying on spatial indicators only. Here, time spent in natural greenspace was very strongly associated with better general health. Participants spending more than 30 min in nature per week reported better general health than those spending no time at all, and these findings were robust to adjustments for influential confounders. Interestingly, this pattern was not observed with time spent in urban greenspace. One plausible explanation is that urban greenspace is mostly found in the central districts of Sofia, where traffic infrastructure is also dense and may thus undermine the benefits of being in greenspace. Conversely, it stands to reason that the role of natural greenspace is driven by the immediate vicinity of the Vitosha Mountain to the South of Sofia. Vitosha Nature Park is a popular touristic and recreational destination offering biodiversity, varied landscape, and opportunities for nature-based activities (Dogramadjieva & Marinov, 2013; Sofia Regional Inspectorate of Environment and Water, 2013). Tests of underlying pathways confirmed the assumption that residential greenspace availability, measured with the NDVI, might foster nature-based physical activity and thereby better general health. Having a home garden was even more robustly associated with time spent in nature, and in turn with better general health. However, direct paths from greenspace to PSRH were not observable in our cross-sectional SEM. The literature strongly supports the mediatory role of green physical activity in generating physical and mental health benefits from being in urban greenspace or in nature (Barton et al., 2016). Having a green yard/domestic garden, whether it is used for gardening activities or simply for enjoying it passively, can reduce depression and anxiety, support physical activity and normal body weight, and generally increase life satisfaction and well-being (Soga et al., 2016; Howarth et al., 2020). Previous studies in Plovdiv, Bulgaria, have also highlighted the role of physical activity as a pathway linking greenspace to better mental health of high school and university students (Dzhambov et al., 2018a, 2018b). Concerning effect modifiers, none were found for NDVI $_{300\ m}$, while home gardens seemed more beneficial to those with lower education and struggling financially. According to one systematic review, greenspace has stronger protective effects for lower-socioeconomic status people (Rigolon et al., 2021), presumably because they may spend more time in their neighborhood due to unemployment or simply rely more on outdoor neighborhood environments as affordable places for social interaction and physical activity, thereby gaining more from existing green infrastructure. Rigolon et al. (2021) have further suggested that in poorer communities the effects of greenspace seem more prominent, as social advantages and health supportive resources mask some benefits of greenspace in wealthier communities. It is difficult to judge the extent to which that is true for our study area.

Poorer general health was reported by people exposed to higher NO_2 at their residence and this association largely survived adjustments for individual and area-level socioeconomic status and urbanicity. This aligns with mounting evidence of the harmfulness of air pollution for physical and mental health (World Health Organization, 2021). Air pollution is a risk factor for a myriad adverse health outcomes, including respiratory disease and cardiovascular disease, diabetes, mental ill-health (Thurston et al., 2017; HEI Panel, 2022), all of which are highly prevalent and affected by air quality in Bulgaria (Health Effects Institute, 2022b). Unlike hard health endpoints, PSRH has rarely been an outcome of interest in the field. In the Klompmaker et al. (2019) study, for instance, one interquartile range increase in NO_2 was

Table 4
Indirect and total effects of greenspace, traffic-elated air pollution, and noise on poor self-rated health (N = 904).

Indirect effects	Estimate	95% CI	
NDVI $_{300\ m}$ → L_{den} air → PSRH	**−0.075***	**−0.130**	**−0.032**
NDVI $_{300\ m}$ → L_{den} rail → PSRH	0.003	−0.010	0.069
NDVI $_{300\ m}$ → L_{den} road → PSRH	0.001	−0.003	0.027
NDVI $_{300\ m}$ → NO_2 → PSRH	0.003	−0.005	0.015
NDVI $_{300\ m}$ → Physical activity → PSRH	−0.005	−0.017	0.002
NDVI $_{300\ m}$ → Time in UGS → PSRH	0.005	−0.001	0.014
NDVI $_{300\ m}$ → Time in nature → PSRH	**−0.020***	**−0.038**	**−0.008**
NDVI $_{300\ m}$ → Time in UGS → Physical activity → PSRH	−0.002	−0.005	0.000
NDVI $_{300\ m}$ → Time in nature → Physical activity → PSRH	**−0.004***	**−0.008**	**−0.001**
Home garden → Physical activity → PSRH	**−0.014***	**−0.029**	**−0.002**
Home garden → Time in UGS → PSRH	0.005	−0.001	0.015
Home garden → Time in nature → PSRH	**−0.028***	**−0.048**	**−0.013**
Home garden → Time in UGS → Physical activity → PSRH	−0.002	−0.006	0.000
Home garden → Time in nature → Physical activity → PSRH	**−0.005***	**−0.011**	**−0.001**
L_{den} road → Physical activity → PSRH	0.001	−0.005	0.008
L_{den} rail → Physical activity → PSRH	0.004	−0.002	0.012
L_{den} air → Physical activity → PSRH	−0.008	−0.020	0.002
NO_2 → Physical activity → PSRH	0.002	−0.008	0.011
Total indirect effect of NDVI $_{300\ m}$	**−0.094***	**−0.155**	**−0.005**
Total indirect effect of home garden	**−0.044***	**−0.070**	**−0.022**
Total effect of NDVI $_{300\ m}$	−0.066	−0.199	0.024
Total effect of home garden	−0.061	−0.151	0.025
Total effect L_{den} road	0.022	−0.042	0.095
Total effect L_{den} rail	**0.119***	**0.039**	**0.220**
Total effect L_{den} air	**0.148***	**0.056**	**0.239**
Total effect NO_2	−0.034	−0.124	0.051

Coefficients are standardized regression estimates with their 95% confidence intervals. Confidence intervals are constructed via bootstrapping (5000 draws). *Coefficient is statistically significant at $p < 0.05$. Abbreviations: L_{den} – day-evening-night sound level; NDVI – normalized difference vegetation index; NO_2 – nitrogen dioxide; PSRH – poor self-rated health, UGS – urban greenspace. Poor self-rated health is an ordered categorical variable, where higher values indicate worse general health status.

associated with 4–7% higher odds of PSRH in single and two-exposure models, respectively. In our study, NO_2 lost its importance when adjusted for multiple traffic noise sources and greenspace, possibly because of their spatial correlations (even though no multicollinearity was indicated). Besides a direct association with PSRH, which finds biological explanation in a number of pathomechanisms involving direct toxicity, oxidative stress, and systemic inflammation (Thurston et al., 2017), we sought to uncover an indirect association between NO_2 and PSRH through lower physical activity, but none was found in the SEM. Our null findings should not discourage future efforts to test the hypothesis that living in a neighborhood with poor air quality might lead to ill-health by inhibiting residents' willingness to spend time in outdoor physical activity. Physical activity has typically been tested as a modifier of air pollution rather than its mediator (cf. Tainio et al., 2021), but a recent Belgian study found that physical activity mediated 30–40% of the effects on PSRH of fine particulate matter, black carbon, and NO_2 (Hautekiet et al., 2022). Evidence of mediation has also been reported with respect to mental health outcomes (Dzhambov et al., 2018c; Wang et al., 2019; Hautekiet et al., 2022). A Bulgarian study using a convenience sample of youth found that NO_2 was related with poorer general mental health through higher annoyance, lower restorative quality, and lower physical activity working in serial (Dzhambov et al., 2018c). Even though effect modification was not confirmed in our study, NO_2 was associated more strongly with PSRH in people facing financial difficulties, which may reflect socioeconomic disparities in air pollution exposure (Hajat et al., 2015; Al Ahad et al., 2022). It is also possible that low-income residents have limited coping resources against air pollution, such as social capital, healthy lifestyle options, and access to healthcare (cf. Braveman and Gottlieb, 2014).

We found a robust association of aircraft noise with PSRH, and mostly such for railway noise. This can be compared to a handful of earlier studies (e.g., Brink, 2011; Halonen et al., 2014; Baudin et al., 2021), none of which, however, collectively tested three sources of traffic noise. In France, male residents living near major airports had 55% higher odds of PSRH per 10 dB(A) L_{den} (Baudin et al., 2021). Klompmaker et al. (2019) modeled two noise sources, reporting 1–2% higher odds per 7.5–8.9 dB(A) road traffic and railway L_{den}, respectively. Given differences in context and noise modeling and general scarcity of evidence, it is difficult to offer easy interpretation of the notably stronger effects of railway and aircraft noise in our study. We reckon that sufficient exposure gradients in our study as a result of the clustered sampling approach may have uncovered these patterns. Moreover, owing to the predominant wind direction in the area, the runway of Sofia Airport is oriented in a way that the acoustic footprint of flight paths is stretched over several residential neighborhoods in the North of Sofia. The densely developed railway and tram network of Sofia is also causing considerable disturbance to local residents. Another plausible explanation could be an interaction between socioeconomic circumstances and these noise sources, as the relationships of railway and aircraft noise with PSRH were more pronounced in less affluent districts of Sofia, and the association with aircraft noise was stronger in less educated residents. As for road traffic noise, unlike here, in a Finnish study, road traffic $L_{den} > 60$ dB(A) versus ≤ 45 dB(A) was associated with 58% higher odds of PSRH, again only in men (Halonen et al., 2014). The only instance in which we observed a significant association with PSRH was in people living in houses with a garden. Since we do not believe this speaks of the harmfulness of home gardens, it is likely this finding reflected underlying correlations in the data, such as better educated people living in downtown buildings without gardens, and others living in individual housing with yards at the outskirts of districts. And indeed, education interacted with road traffic L_{den} generating larger effect estimates in less educated people. To that we can add that the narrower range of road traffic L_{den} and lack of low exposure levels may have reduced the statistical precision of these effect estimates. Another likely explanation for the null effect of road traffic noise is exposure misclassification caused by using crude polygon maps for road traffic noise (cf. Khomenko et al., 2022) and not accounting for additional building characteristics. Disregarding individual vulnerability (sensitivity) and psychosocial stressors or resources in the neighborhood could have added to that (Riedel et al., 2015). Non-acoustic factors in particular have the potential to modify or mediate the effects of traffic noise (Riedel et al., 2021). In the study by Fyhri and Klaeboe (2009), SEM showed no relationships between road traffic noise and health complaints in Oslo, but a clear role of noise sensitivity.

Rugel and Brauer (2020) have found limited research that properly accounted for the complexity of relationships between multiple urban exposures and physical health. Therefore, our study aimed to expand the evidence on the subject. Following in the footsteps of Klompmaker et al. (2019), we conceived alternative interrelationships between greenspace, NO_2, and noise. Interaction tests indicated that when road traffic L_{den} was >60 dB(A), the relationship between aircraft noise and PSRH was steeper. As regards mediation, in the study of Klompmaker et al. (2019), the association of NDVI $_{300\ m}$ with PSRH was partly mediated by NO_2, while L_{den} was not tested, because the authors used simplistic analytical approaches and criteria for establishing presence of mediation. In our SEM, greenspace, aircraft, and railway noise were all influential predictors of PSRH, but besides a pathway from NDVI $_{300\ m}$ through lower aircraft L_{den}, no indirect pathways through other exposures were apparent. The reasons for this could be strong covariances in the SEM, which though accounted for, may have concealed paths from NDVI $_{300\ m}$ through NO_2 and rail traffic L_{den}, which were implied in tests of bivariate correlations.

4.2. Strengths and limitations

The current study has a number of strengths that we believe outweigh its limitations. It advances the field locally, being the first population-based Bulgarian study to examine the health impacts of multiple exposures. The sampling design made the data mostly representative of the sociodemographic structure of the population and spatial distributions of exposures across Sofia. Another strength is that we considered multiple exposures simultaneously, including a number of spatial indicators of greenspace, NO_2, and traffic noise. In addition to the mere presence and access to greenspace, we had information on home gardens and actual time spent in both urban and natural greenspace, which enabled us to disentangle their effects. Next, the intertwining of all three exposures was modeled through complementary statistical approaches – single- and multi-exposure regressions, interaction tests, and mediation analysis. The SEM approach specifically is still underutilized in greenspace epidemiology, and even more so in the air pollution and noise fields (cf. Dzhambov et al., 2020). Here, mediation by physical activity was contemplated with respect to not just greenspace, but NO_2 and traffic noise as well. Finally, we accounted for both individual and area-level income, which is not always possible in environmental health studies.

Several limitations, however, are noteworthy. To begin with, by design, a cross-sectional study cannot establish true causality in the data. To mitigate this, we included only respondents who had not changed their place of residence for the least five years, therefore the majority of included participants were long-term non-movers. We also extracted information on spatial exposures for time periods preceding questionnaire data collection. Nevertheless, one can argue that this approach may have dispelled immediate concerns about residential self-selection, but not about the direction of associations between PSRH and self-reported measures of physical activity and time spent in greenspace. It is possible that people reporting better general health at the time of the survey were also more likely to be physically active outdoors.

Next, even though our sample's characteristic reflected the general patterns in the population of Sofia in the age range 18–65 years, we had slightly more ethnic Bulgarians and university graduates, more people reporting "Satisfactory health" and fewer "Very good health", less middle-aged and more 60–65-year-olds (Table S2). Ethnic minority members were underrepresented in the sample and they are more likely to live in polluted communities and have poorer access to healthcare, therefore, we could have observed stronger effects of road traffic L_{den} and NO_2 had our sample been representative on that characteristic. The response rate was also modest due to our strict inclusion criteria (five years of residence and specific exposure profile), which limited the pool of potential respondents. That could have contributed to lower external validity of our study.

Out of the three pathway domains proposed to link greenspace to health (i.e., mitigation, restoration, and instoration) (Markevych et al., 2017), we did not include a measure of the restoration/stress reduction pathway. Unlike previous studies in Bulgaria (Dzhambov et al., 2018a, 2018b, 2018c), the current study was not specifically designed to tap environmental perceptions or neighborhood restorative quality. As a result, we only had relatively crude single-item measures of perceived environmental characteristics (e.g., greenness, quietness, safety, annoyance), but did not measure perceived restorative quality. Given our already complex conceptual model, we decided to focus on pathways involving use of greenspace and physical activity. Nevertheless, the restoration pathway has mostly been evaluated with mental health/well-being as the outcome (Dzhambov et al., 2020) and it would be valuable to design a study where these temporally unstable mechanisms can be captured with respect to outcomes that take longer periods of time to unfold.

Physical activity was measured with three simple items combined into total time spent in physical activity per week. A more detailed assessment of different types of physical activity and corresponding excretion levels could have enabled observing significant indirect effects of L_{den} and NO_2 on PSRH via physical activity, which we originally hypothesized.

Earlier studies adjusted their models for behavioral risks like smoking status and alcohol consumption (Klompmaker et al., 2019), but we deliberately excluded those variables from our analyses, as we tend to align with more conservative views on confounding (i.e., that a confounder should be antecedent to both the exposure and the outcome) (cf. VanderWeele and Shpitser, 2013). Actually, smoking (e.g., Dzhambov et al., 2022) and adiposity (Luo et al., 2020; Gui et al., 2022; Shi et al., 2022) can be seen as additional mediators between environmental exposures and health, but we preferred to keep our model parsimonious given its already complex structure.

Though it has been planned to model particulate matter at a fine spatial resolution for the entire territory of Sofia, this study could only make use of reliable estimates of long-term NO_2. Fine particulate matter is associated with a much larger disease burden (Health Effects Institute, 2022a) and may follow different spatial patterns than NO_2 in Sofia, therefore it could have revealed stronger effects on PSRH. Another limitation has to do with the noise data, which were extracted from the EU strategic noise maps of Sofia. Since those maps were delivered in polygon format, their quality was suboptimal for health research purposes, unlike raster maps with continuous L_{den} distributions (Khomenko et al., 2022). We believe this has mostly caused non-differential exposure misclassification in terms of road traffic L_{den}, which was assigned based on an intersection of the address location with the nearest noise polygon. Hence, spill-over effects from adjacent locations, coupled with a coarse exposure resolution on an ordinal scale, have likely undermined the precision of the noise estimates. On the other hand, with railway and aircraft noise, polygon maps seemed to present less of a problem, as purposeful selection of survey sampling locations (based on distances to Sofia Airport and railway/tram lines) allowed constructing exposure variables with sufficient range. Finally, we did not collect information on noise sensitivity, and as already noted it is an important non-acoustic factor to consider in noise studies (Fyhri and Klaeboe, 2009; Riedel et al., 2021).

4.3. Urban planning and development implications for Sofia, Bulgaria

Sofia has experienced construction boom, infill, and suburban development in the last few decades. That has led to fragmented and degraded access to greenspace, accompanied with high levels of motorization and noise. The results of this study could inform decision-makers, urban planners, and civil society organizations in areas of transport, air quality, public health, and urban development in general. Designing mitigation and abatement policies and measures should take into account the socioeconomic status of citizens and target those with lower education and financial difficulties.

Given the strong associations of aircraft and railway noise with poor general health we observed, our study could raise awareness of the health effects of noise and stimulate exposure scientists to produce more refined acoustic models of the city that could serve research purposes. This is particularly relevant since 99% of the population is exposed to harmful road traffic noise levels coupled with crude resolution of existing noise maps (Khomenko et al., 2022). However, residents are exposed to other noise sources beyond road traffic because of the presence of a large international airport with flight paths over residential neighborhoods and well-developed railway and city tram lines, most of which lack proper noise abatement and shielding.

In terms of air pollution, Sofia is located in a mountain valley, surrounded by the Balkan Mountains to the North and Vitosha, Lyulin, Plana, and Lozenska Mountains to the South, which causes temperature inversions and periods of poor ventilation, resulting in buildup of air pollution. Air pollutants are generated in various ways, concentrated or dispersed due to heavy traffic and congestion along urban highways and several boulevards as well as typical and more specific street canyons in between continuous central and discontinuous secondary centers with intensive building morphology. There are internal and external peripheries surrounding the city with numerous domestic heating sources of pollution contributing seasonally, but also green wedges and small rivers ventilating adjacent parts of the city.

At the same time, the proximity of Vitosha Mountain and the eponymous Nature Park, along with other surrounding recreational landscapes, provide citizens with an escape from environment stressors. Though, reaching those areas in peak seasons and hours on the weekend can be a stressful experience in itself. Our findings lend support to the implementation of the so-called Green Wedges planned in Sofia's Master Plan (Municipality Sofia, 2009; PwC Advisory spółka z ograniczoną odpowiedzialnością sp.k, 2020). These will include parks that stretch from Vitosha, Lyulin, and Plana Mountains along small rivers towards the city center and the northern lower lying districts with poor accessibility through the railways, serving as barriers. They will confer multiple ecosystem services, such as providing places for sport and recreation, and regulation of local climate, including fresh mountain air influx and improved ventilation of the city. Well-designed greenspace with better public access can stimulate active commuting and serve recreational purposes. The German architect and urban designer Adolf Muesmann has planned them already in 1938, but today, due to restitution of private ownership of the land on their long path of provision, their realization is at risk.

Active mobility and lifestyle are in pressing need of better regulation and stronger support to alternatives to car-dominated mobility. Therefore, protected, safe, and dense cycling infrastructure and accessible, convenient, clean, calm, and quiet pedestrian network, as parts of healthy green corridor provisions in many of the city districts, can be a game-changing transformation.

5. Conclusions

Living in a greener neighborhood and having a home garden were inversely associated with poor general health in Sofia, while higher traffic-related air pollution, and especially aircraft and railway noise were associated with worse general health. The relationships between greenspace and home gardens with better general health were mediated by spending more time in nature and higher physical activity. These results could inform decision-makers, urban planners, and civil society organizations in areas of transport, air quality, and public health in Sofia and other cities facing similar urban development problems. Designing mitigation and abatement policies and measures should take into account the socioeconomic status of citizens and target those with lower education and financial difficulties.

Author statement

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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.

Data availability

The authors do not have permission to share data.

Acknowledgements

This study was funded by the Bulgarian National Science Found (BNSF), under project "Development of a methodology for assessing air quality and its impact on human health in an urban environment" (№ КП-06-Н54/2–15.11.2021).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2023.116087.

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