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Daily space-time activities, multiple environmental exposures, and anxiety symptoms: A cross-sectional mobile phone-based sensing study

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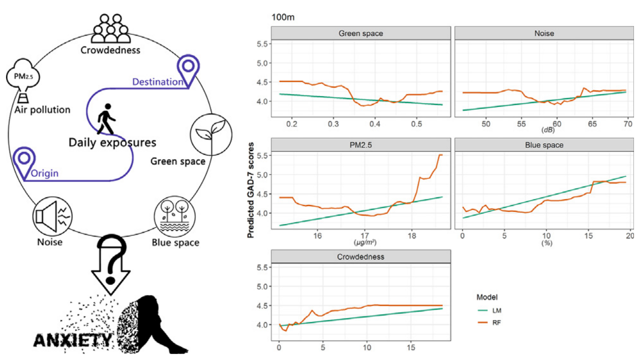
HIGHLIGHTS

- Environmental exposures were assessed along people's GPS-tracked mobility paths.
- Anxiety was negatively related with green space and positively related with crowdedness.
- Null linear associations were observed between environmental exposures and anxiety.
- Random forest showed that associations varied nonlinearly with exposure levels.
- Random forest ranked environmental exposures as more important to explain anxiety.

GRAPHICAL ABSTRACT



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ABSTRACT

Background: Few mobility-based studies have investigated the associations between multiple environmental exposures, including social exposures, and mental health.
Objective: To assess how exposure to green space, blue space, noise, air pollution, and crowdedness along people's daily mobility paths are associated with anxiety symptoms.
Methods: 358 participants were cross-sectionally tracked with Global Positioning System (GPS)-enabled mobile phones. Anxiety symptoms were measured at baseline using the Generalized Anxiety Disorder-7 (GAD-7) questionnaire. Green space, blue space, noise, and air pollution were assessed based on concentric buffers of 50 m and 100 m around each GPS point. Crowdedness was measured by the number of nearby Bluetooth-enabled devices detected along the mobility paths. Multiple linear regressions with full covariate adjustment were fitted to examine anxiety-environmental exposures associations. Random forest models were applied to explore possible nonlinear associations and exposure interactions.
Results: Regression results showed null linear associations between GAD-7 scores and environmental exposures. Random forest models indicated that GAD-7-environment associations varied nonlinearly with exposure levels. We found a negative association between green space and GAD-7 scores only for participants with moderate green space exposure. We observed a positive association between GAD-7 scores and noise levels above 60 dB and air pollution concentrations above 17.2 μg m^{-3}. Crowdedness was positively associated with GAD-7 scores, but exposure-response functions flattened out with pronounced crowdedness of >7.5. Blue space tended to be positively associated with GAD-7 scores. Random forest models ranked environmental exposures as more important to explain GAD-7 scores than linear models.
Conclusions: Our findings indicate possible nonlinear associations between mobility-based environmental exposures and anxiety symptoms. More studies are needed to obtain an in-depth understanding of underlying anxiety-environment mechanisms during daily life.

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1. Introduction

Anxiety is among the most prevalent public health issues (Vos et al., 2020). Globally, 301 million people were diagnosed with anxiety in 2019, representing a 55% increase compared with 1990 (Yang et al., 2021). Reviews and meta-analyses have provided evidence that certain features of the environment are associated with anxiety symptoms. Harmful exposures include air pollution (Braithwaite et al., 2019) and noise (Lan et al., 2020), while green space (Wendelboe-Nelson et al., 2019) and blue space (Smith et al., 2021) seem to be health-supportive. Social environmental factors were also associated with anxiety (Alegria et al., 2018) but are less often included together with environmental exposures. For example, having a low income, limited education, poor neighborhood conditions (Lund et al., 2018), and crowdedness (Cheng, 2010) may contribute to anxiety.

Most studies have assessed exposures exclusively around people's residences (Helbich et al., 2020; Klompmaker et al., 2019; Schmitt et al., 2021). However, because people only spend, on average, less than two-thirds of their daily life at home (Khajehzadeh and Vale, 2017), residence-based approaches may oversimplify people's true exposure by ignoring environments beyond the home (Helbich, 2018; Kwan, 2012, 2018a). Usually, people also experience exposures along their travel path and at their activity places (Poom et al., 2021; Vallée, 2017). According to the neighborhood effect averaging problem (Kwan, 2018b), residence-only assessments tend to overestimate or underestimate people's exposures because they are more likely to then visit areas with exposure levels different from their homes. Thus, residence-only exposure assessments likely misclassify exposures that possibly bias environment-health associations. To mitigate this problem, personal exposure assessments along people's daily moving trajectories are advocated (Chaix, 2018; Kwan, 2012).

Global Positioning System (GPS)-enabled sensing technologies, either through mobile phones or portable devices, provide unique opportunities to objectively monitor people's mobility patterns and their activity locations accurately in space-time (Birenboim et al., 2021), which enables more precise exposure assessments (Chaix, 2018). As yet, with a few exceptions (Kou et al., 2020; Roberts and Helbich, 2021; Tost et al., 2019), mental health research has ignored mobility-based exposure assessments and at least the following two limitations remain.

First, most mobility-based studies investigated a single environmental exposure on mental health (Jiang et al., 2020; Tost et al., 2019), only a few considered the co-occurrence of multiple environmental factors (Kou et al., 2020; Roberts and Helbich, 2021). Though assessed in a residential setting, single exposure models likely overestimate exposure effects (Klompmaker et al., 2019) because different environmental factors are spatially correlated and potentially confound each other (Rugel and Brauer, 2020).

Second, the simultaneous consideration of social contexts within the environment throughout the day is lacking (Alexandre et al., 2020). Crowdedness, for example, varies spatiotemporally throughout the course of a day depending on people's activity places. Elsewhere it was shown that crowdedness can risk psychological distress (Evans and Ferguson, 2011) and anxiety (Cheng, 2010), especially in places (e.g., overcrowded dwellings, public transport) where it is infeasible to regulate interpersonal distance freely (Geraets et al., 2018).

To address these research gaps, our primary aim is to assess how exposure to green space, blue space, noise, air pollution, and crowdedness along people's daily mobility paths are associated with anxiety symptoms. Based on a sample of GPS-tracked Dutch adults, we tested for the first time the hypotheses that: 1) higher levels of air and noise pollution experienced throughout the day correlate positively with more anxiety symptoms; 2) higher levels of green and blue space are inversely correlated with anxiety symptoms; 3) crowdedness is associated with more anxiety symptoms. As a secondary objective, we examined the importance of these environmental exposures to better understand their relative roles in terms of people's anxiety symptoms.

2. Materials and methods

2.1. Study design and survey

The Netherlands is a densely populated, highly-urbanized country, and most cites are historically grown with only a few high-rise buildings (Kuitenbrouwer and De Saeger, 2015). We conducted a cross-sectional analysis as part of the NEEDS ('Dynamic Urban Environmental Exposures on Depression and Suicide') project. Details on the study protocol are published elsewhere (Helbich, 2019). Briefly, eligible for survey participation were those registered in the Dutch National Personal Records Database, aged between 18 and 65 years, living in a private household, and not sampled by Statistics Netherlands in the past year. We sampled 45,000 people from the eligible target population using a multi-stage sampling procedure during September–November 2018 (Helbich, 2019). To maximize study participation, two postal reminders were sent; and incentives were raffled. Out of those invited, 11,505 respondents completed the survey on personal characteristics and mental health, yielding a response rate of 25.6%.

2.2. Mobile phone-based data collection

Those who completed the survey and agreed to be re-contacted were invited up to two days after the survey completion via email to download our "Jouw Leefomgeving" mobile phone app. Aligned with previous studies (Kestens et al., 2018; Kondo et al., 2020), the app stopped recording after 7 days of data had been collected cumulatively. We raffled 400 vouchers each worth €22 to increase study participation in the mobile phone-based data collection (Helbich, 2019). A total of 821 participants (7.1% of survey respondents) downloaded the app.

2.2.1. GPS data

We obtained respondents' GPS-based locational information every 20 s. The recording frequency decreased to 1 min when the phone was stationary (i.e., displacement of the phone <20 m) for longer than 30 min. If there was no relevant movement over 1 h, the recording frequency decreased further to 2 min to save battery. 629 of the respondents gave permission for the app to record their locations and provided at least one measurement.

2.2.2. Bluetooth data

Mobile phones can detect nearby Bluetooth signals within 5–10 m (Eagle and Pentland, 2006). As Bluetooth technology is commonly used in portable devices (e.g., mobile phones, earphones), it is reasonable that more signals will be detected in more crowded places. To approximate the crowdedness people experienced during their routine mobility (Eskes et al., 2016; Nicolai and Kenn, 2006), the number of nearby Bluetooth-enabled devices was recorded along the mobility paths. Bluetooth scanning was done every 15 min due to its pronounced battery demand. 610 participants allowed Bluetooth scanning.

2.3. Preprocessing of the GPS locational information

GPS data preprocessing included four steps (Roberts and Helbich, 2021). First, we excluded participants that had fewer GPS locations than 2.5 times the median absolute deviation, because we deemed their numbers of GPS observations as outliers in our sample (Leys et al., 2013). Second, participants with any GPS points outside the Netherlands were removed as their data did not represent a typical week. Third, GPS points with a speed of >200 km/h were removed. This speed was deemed implausible in the Dutch context (Bohte and Maat, 2009). Fourth, because GPS accuracy can decrease from about 5–10 m to over 50 m due to high-rise buildings or during travel, GPS points located farther than 50 m from the travel network were discarded (Beekhuizen et al., 2013). The travel network consisted of roads, railways, pedestrian paths, and bike paths and was obtained from the digital Dutch topographic map 1:10,000 (Kadaster, 2020).

After GPS data cleaning (Table S1 in the Supplementary materials), 358 participants remained in our sample. As we have no exposure data for

Germany and Belgium, the GPS points located within 100 m of the border were excluded (0.08% of all GPS measurements) to avoid edge effects. On average, each participant contributed 6.89 days of data. In total, we included 589,079 GPS points. 50.5% of GPS points were collected outside participant's residential environment (i.e., 500 m buffer area of home address) (Table S2). The sample was largely similar in terms of the demographics and socio-economic characteristics before and after the data cleaning (Table S3).

2.4. Anxiety symptoms as an outcome measure

Symptoms of anxiety in the past two weeks were measured using the Generalized Anxiety Disorder-7 (GAD-7) questionnaire (Spitzer et al., 2006). The GAD-7 includes 7 items, each of which can be scored on a four-point scale between 0 ("Not at all") to 3 ("Nearly every day"). Participants were asked, for example, how often they have been bothered by problems such as "Feeling nervous, anxious or on edge" and "Not being able to stop or control worrying" over the past two weeks. To obtain an overall GAD-7 score, the individual item scores were summed. A higher total score indicates more severe anxiety symptoms with the overall score ranging from 0 to 21. The Cronbach's alpha was 0.91, signifying excellent internal consistency.

2.5. Environmental exposures

2.5.1. Exposure assessment

Environmental exposures were assessed based on concentric buffers of 50 m and 100 m around each GPS point. Earlier studies (Mueller et al., 2020; Roberts and Helbich, 2021) used similar buffer sizes to represent the immediate environment that participants had direct contact with.

2.5.2. Green space

We used the Normalized Difference Vegetation Index (NDVI) as the green space metric (Tucker, 1979). The NDVI was derived for the year 2018 from all available Landsat 8 scenes at a 30 m spatial resolution via Google Earth Engine (Gorelick et al., 2017). We only included images collected from May to September when vegetation is greenest. Scenes were atmospherically corrected; those with >40% cloud cover and pixels with a cloud score of >25 were excluded. NDVI values range from −1 to 1; higher positive values indicate more vegetation. To reduce distortion caused by negative values, pixels with negative NDVI scores were masked before calculating the mean NDVI value per buffer.

2.5.3. Blue space

Data for blue space, defined by fresh- and saltwater, were extracted from the Dutch land-use database for 2018 (Hazeu et al., 2020). This dataset represents 48 land use categories with a 5 m spatial resolution. Blue space exposure was calculated as the proportion of pixels that were defined as blue space per buffer.

2.5.4. Air pollution

Estimated annual average particulate matter with an aerodynamic diameter of 2.5 μm ($PM_{2.5}$) in μg m^{-3} was derived from a nationwide land-use regression (LUR) model. The initial land-use regression was calibrated for 2009 based on land use, traffic infrastructure, traffic intensity, and population density at a spatial resolution of 5 m (Schmitz et al., 2019) which was aggregated to 25 m. Elsewhere it was shown that annual mean air pollution concentrations were rather stable over a decade (de Hoogh et al., 2018).

2.5.5. Noise pollution

Noise data from the Standard Model Instrumentation for Noise Assessments (STAMINA) capture average day-night-evening (Lden [dB]) noise levels based on noise sources emitted from roads, rails, air traffic, industry, and wind turbines for 2016 (National Institute for Health and Environment, 2019). The spatial resolution of the map depends on the distance between the source and the observation point, ranging from 10 m (close to the source) to 80 m (Schreurs et al., 2010). Estimates were categorized into 9 classes ranging from <45 dB to >80 dB with an interval of 5 dB. Noise exposure per circular buffer was assessed by weighting each assigned value based on the proportion of the class within the buffer and summing.

2.5.6. Crowdedness

The number of Bluetooth-enabled devices in the 5–10 m proximity of each participant every 15 min served as a proxy variable for experienced crowdedness. We averaged the number of detected devices over the data collection period.

2.6. Covariates

We included survey-based covariates which were used previously in mental health studies (Alegria et al., 2018; Lund et al., 2018). Person-level covariates included age (in years), sex (male, female), origin (Dutch, other Western countries, non-Western countries), educational background (low [up to lower secondary education], medium [up to upper secondary education], high [university education and further]), employment status (employed, unemployed), marital status (married, unmarried), household type (couple with children, couple without children, single parent, other household types), and income quintiles which were treated as continuous (higher score indicating higher income).

On the residential level, we adjusted for population density, socio-economic deprivation, and perceived neighborhood quality. Population density and socio-economic deprivation were derived by aggregating microdata for the entire Dutch population per address on 1st January 2016 (Helbich, 2019). We geocoded participants' home addresses and superimposed buffers of 50 m and 100 m before assessing population density and deprivation. Population density was measured by the number of residents within the buffers. As the distribution of population density was skewed, we log-transformed this covariate. Deprivation was measured through summing the *z*-scores of the unemployment rate, the reverse coded standardized median household income, and the share of households with a standardized income below the poverty line. A higher total score indicated greater deprivation. Perceived neighborhood quality (e.g., litter on the street) was assessed using the four-item "pleasantness" module and the last item of the "maintenance" module from the Instruments for Assessing Levels of Physical Activity and Fitness (ALPHA) questionnaire (Spittaels et al., 2009). Participants rated their agreement with each statement on a Likert scale from 1 ("Strongly disagree") to 4 ("Strongly agree"). Negative items were inversely recoded so that higher score represent better neighborhood quality. The individual item scores were summed to obtain the overall scores (ranging from 4 to 20), with higher score representing better neighborhood quality.

2.7. Statistical analyses

GPS and Bluetooth data were nested within a respondent, but the outcome was measured only once, resulting in a micro-macro data structure (Croon and van Veldhoven, 2007). To align the exposure data with the survey data, exposures were aggregated per person (Roberts and Helbich, 2021). Rather than averaging the data directly, which would reduce data variability and bias subsequent modeling results (Croon and van Veldhoven, 2007), we calculated the unbiased group mean by producing a latent variable per exposure, where the nested exposure assessments were treated as indicators of the exposure for each participant.

Following descriptive and bivariate analyses (i.e., Wilcoxon tests, Spearman correlation coefficients), we developed multiple regression models to investigate the associations between GAD-7 scores and environmental exposures. Models were fitted with full covariate adjustment. Because the difference in the number of GPS points per participant could cause heteroscedasticity, White's correction was applied to the regression results. Generalized variance inflation factors (GVIF) assessed covariate multicollinearity. GVIFs > 10 were problematic. We also did stratified analyses based on demographic and socioe-conomic characteristics of the sample.

Our initial regression analyses did not take variable interactions into account while assuming linear health-exposure associations. To overcome these restrictions, we additionally calibrated covariate-adjusted random forest (RF) models with GAD-7 scores as the outcome variable. A RF model has the advantages of capturing nonlinear associations, modeling a priori unknown variable interactions, avoiding overfitting, while not relying on strict modeling assumptions (Breiman, 2001). The parameters of the RFs were based on 10 times repeated 10-fold cross-validation. We systematically tested the number of random variables included at each split and evaluated the cross-validation-based root mean square error (RMSE) and mean absolute error (MAE). RF models have been shown to perform favorably in their predictive performance across several datasets against other machine learning algorithms (Fernández-Delgado et al., 2014; Helbich et al., 2020). Our performance comparison (Fig. S1) among RF and Gradient Boosting Machine (GBM) also indicated that RF performed well in our case. We used partial dependence plots (Friedman, 2001) to assess possible nonlinearities in the health-exposure associations. To determine variable importance, we used a permutation-based approach by measuring the change in model performance. All analyses were conducted in R3.6.2 (R Core Team, 2019).

3. Results

3.1. Descriptive statistics

Table 1 describes the study sample. Most participants showed minimal to mild anxiety symptoms (GAD-7 ≤ 5). The mean GAD-7 score for the 358 respondents was 4.04 ± 4.36; the Wilcoxon test indicated that the GAD-7 scores were not significantly ($p = 0.706$) different from the whole survey sample ($N = 11{,}505$) (Mean: 4.15 ± 4.41). The mean age of the respondents was 44.33 ± 14.26 years, 46.3% were female, 52.6% were married, 69.9% were employed, 48.2% were highly educated, and 90.1% were of Dutch origin with 62% were in the high or very high income (Table S3). The mean neighborhood quality was 11.765. Population density was significantly higher with 100 m buffers, but deprivation was comparable across buffer sizes ($p = 0.444$).

Table 1
Characteristics of the sample.

Variables	Category	Final sample (N = 358)
GAD-7 score	Mean (SD)	4.045 (4.361)
Age	Mean (SD)	44.201 (14.156)
Sex	Male [*N* (%)]	195 (54.5%)
	Female [*N* (%)]	163 (45.5%)
Employment	Employed [*N* (%)]	250 (69.8%)
	Unemployed [*N* (%)]	108 (30.2%)
Education	Low [*N* (%)]	43 (12.0%)
	Mid [*N* (%)]	139 (38.8%)
	High [*N* (%)]	176 (49.2%)
Marital statues	Married [*N* (%)]	192 (53.6%)
	Unmarried [*N* (%)]	166 (46.4%)
Household type	Couple with child [*N* (%)]	169 (47.2%)
	Couple without child [*N* (%)]	112 (31.3%)
	Other household type [*N* (%)]	60 (16.8%)
	Single parent [*N* (%)]	17 (4.7%)
Origin	Dutch [*N* (%)]	323 (90.2%)
	Western [*N* (%)]	25 (7.0%)
	Non-western [*N* (%)]	10 (2.8%)
Income	Mean (SD)	3.628 (1.254)
Neighborhood quality	Mean (SD)	11.765 (1.541)
Logged population density (50 m)	Mean (SD)	4.040 (0.685)
Logged population density (100 m)	Mean (SD)	5.277 (0.691)
Deprivation (50 m)	Mean (SD)	−0.019 (1.786)
Deprivation (100 m)	Mean (SD)	0.087 (1.889)

Table 2
Mobility-based environmental exposures of the sample.

	50 m buffer size	100 m buffer size	*p*-Value
Green space [mean (SD)]	0.356 (0.063)	0.369 (0.064)	0.010
Blue space (%) [mean (SD)]	2.626 (2.482)	3.174 (2.854)	0.006
Noise (dB) [mean (SD)]	61.071 (4.176)	60.352 (3.910)	0.018
$PM_{2.5}$ (μg m^{-3}) [mean (SD)]	17.011 (0.714)	16.912 (0.669)	0.056
Crowdedness [mean (SD)]	3.098 (2.608)	3.098 (2.608)	N.A.

Summary statistics of mobility-based exposures are in Table 2. Mean green space and blue space were slightly higher for 100 m buffers than for the 50 m buffer, but mean noise and $PM_{2.5}$ were slightly lower. Differences for green space, blue space, and noise were statistically significant ($p < 0.05$).

3.2. Bivariate analysis

Fig. 1 shows the Spearman correlations between GAD-7 and the mobility-based exposures. Exposures across the buffer sizes were highly correlated ($r = 0.96$ to 0.99). GAD-7 was significantly and negatively correlated with green space ($r = -0.11$ to -0.13, $p < 0.05$) and positively correlated with crowdedness ($r = 0.13$, $p < 0.05$); correlations with blue space, noise, and $PM_{2.5}$ were insignificant. Most exposure correlations were weak ($|r| < 0.4$); only correlations between noise and $PM_{2.5}$ were moderately high ($r = 0.45$ to 0.49). Green space was inversely correlated with noise, $PM_{2.5}$, and crowdedness. Blue space was positively correlated with noise; correlations with green space, air pollution, and crowdedness were largely insignificant. Noise was positively correlated with $PM_{2.5}$ and crowdedness. The air pollution-crowdedness correlation was positive.

3.3. Associations between mobility-based environmental exposures and anxiety symptoms

The largest GVIF was 2.22, signifying no covariate multicollinearity. Wald tests indicated no significant differences in the magnitude of the regression coefficients across the 50 m and 100 m buffers (all $p > 0.05$). Fig. 2 shows the regression coefficients of environmental exposures. All mobility-based exposures were insignificantly associated with anxiety symptoms. The signs of the coefficients (Table S4) indicated that green space tended to be negatively associated with anxiety symptoms, while blue space, noise, air pollution and crowdedness tended to be positively associated. Stratified analyses did not alter these results (Table S5).

Fig. 3 shows the partial dependence plots of the RF for the 100 m buffer models. Associations were largely comparable across the 50 m and 100 m buffers (Fig. S2) and across the other machine learning algorithms (Fig. S3). The RF-based partial dependent plots show some nonlinearities in the associations, insufficiently captured in the linear model. The negative anxiety-green space association was only observed for participants with green space exposure ranging from 0.25 to 0.37. In the 100 m model, a sharp drop in GAD-7 scores was observed when the level of green space increased from 0.32 to 0.37. The association between noise and anxiety varied with the exposure level; the association was positive only for those with noise levels beyond 60 dB. Air pollution showed a similar pattern; a pronounced positive association was observed for participants with higher exposure levels (>17.2 μg m^{-3}). Aligned with the linear regression, participants with higher blue space exposure had higher GAD-7 scores. Exposure to more crowded environments was associated with a higher GAD-7 score; but the positive association flattened when the level of crowdedness was higher than 7.5.

3.4. Importance of environmental exposures

Fig. 4 shows the variable importance ranking based on RMSE change using permutation-based approach (Table S6). The RF and linear models ranked the variables differently, though both yielded rather similar ranks across the buffer sizes. Environmental exposures tended to be of less relevance than individual-level variables (e.g., age, origin, sex, income) in the linear model. In contrast, most environmental exposures (e.g., green space, $PM_{2.5}$, crowdedness, noise)

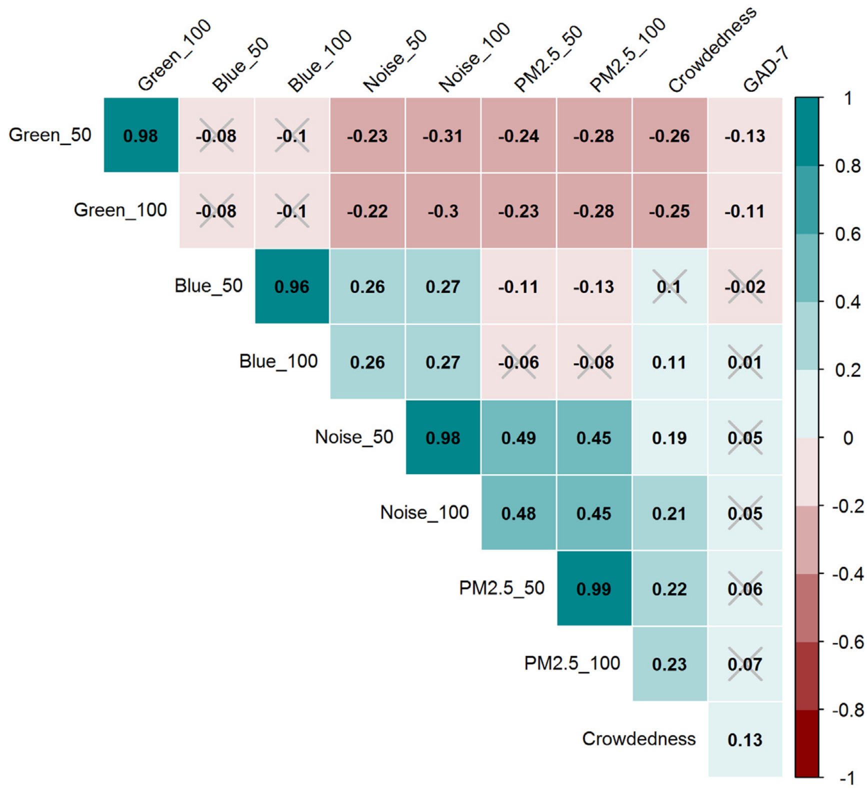

Fig. 1. Correlation matrix of the mobility-based exposures based on Spearman correlation coefficients. Note that "50" and "100" refers to the buffer size used. Cells marked with "X" refer to insignificant correlations ($p > 0.05$).

appeared more relevant in the RF models, whereas sex, neighborhood quality, employment, and origin were less important in the RF.

4. Discussion

4.1. Potential mechanisms and comparisons with previous studies

4.1.1. Green space

Our linear models did not support the expected benefits of green space exposure on anxiety symptoms. We objectively measured the availability of green space during people's daily mobility using the NDVI, while other aspects, such as subjectively perceived greenness (Kruize et al., 2020), types (Akpinar et al., 2016; Jarvis et al., 2020), quality (L.Q. Zhang et al. 2021), and use (Coldwell and Evans, 2018) of green space have been shown to promote health. Previous studies that have focused on multiple mental health disorders have more often found a relationship between green space and depression, rather than anxiety (White et al., 2021). A comparative mobility-based Dutch study also reported a significant association between green space and depression symptoms (Roberts and Helbich, 2021). According to our RF models, the negative association between green space and anxiety was only found for moderate NDVI levels (0.32 to 0.37), which could also contribute to the insignificant associations

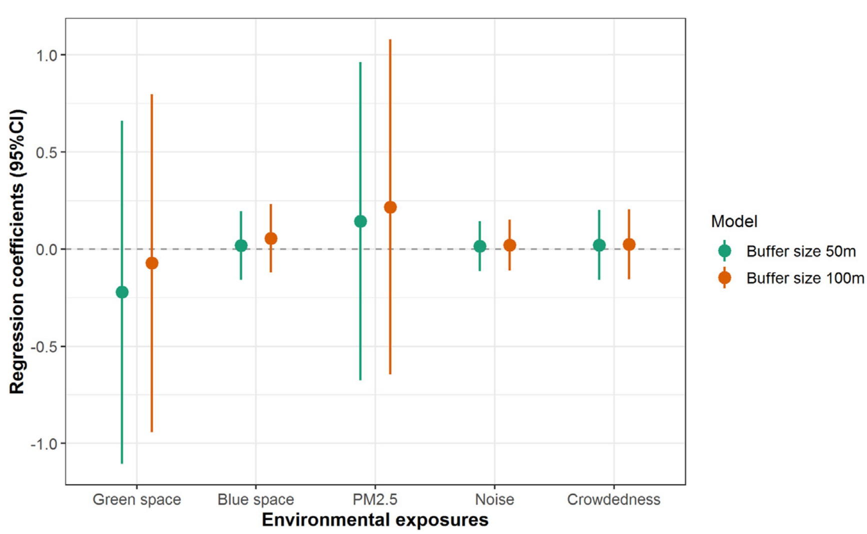

Fig. 2. Regression coefficients for linear associations between GAD-7 scores and the mobility-based environmental exposures. The models were adjusted for age, sex, origin, educational background, employment status, marital status, household type, income, perceived neighborhood quality, population density and socio-economic deprivation of the residential area.

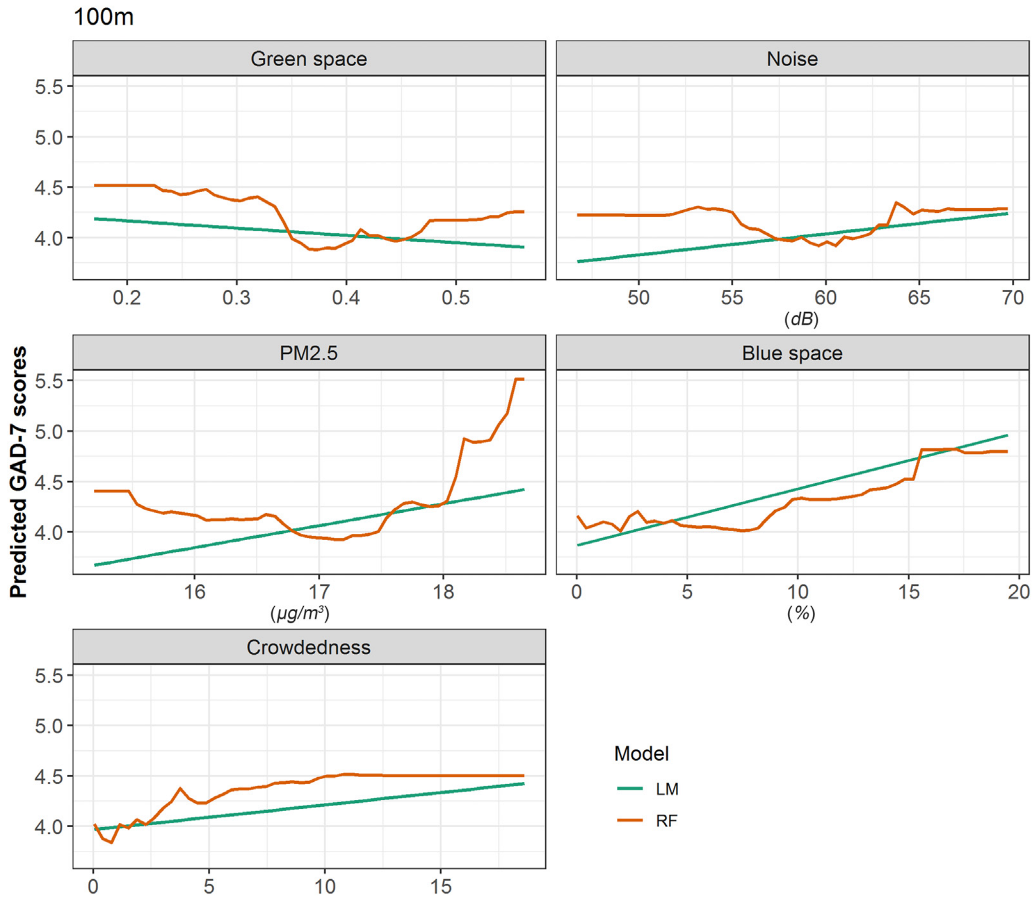

Fig. 3. Partial dependence plots of the GAD-7-environmental exposure associations based on 100 m buffers using linear regression model (LM) and random forest (RF).

observed in the linear models. It is possible that these low levels of green space exposure are insufficient to support mental health.

Green space benefits mental health by relieving chronic stress and preventing systemic physiological dysregulation (Beemer et al., 2021). Most previous evidence on the anxiety-green space association is from residential-based studies and results remain inconsistent. Our results differ from some studies showing that increasing levels of exposure to green space was associated with reduced anxiety risk (Dzhambov et al., 2019). However, as in our study, several also reported null association (Gascon et al., 2018; Pelgrims et al., 2021), including some studies in the Netherlands (Generaal et al., 2019; Helbich et al., 2021).

4.1.2. Blue space

Contrary to our hypothesis, linear models showed null associations between blue space and anxiety. This could be a consequence of not distinguishing the effects of different types of blue space (McDougall et al., 2020). A study based on 18 countries reported a positive association between visiting inland blue space and anxiety but a null association for visiting coastal blue space (White et al., 2021). Another US-based ecological study found protective effects for distance to a Great Lake, but the distance to nearest small inland lakes was positively associated with anxiety disorder hospitalizations (Pearson et al., 2019). RF models indicated a nuanced and overall positive relationship. One possible explanation is that people with severe anxiety symptoms may visit blue space more often for self-regulation purposes.

Theoretically, blue space is believed to reduce mental illness through similar pathways as green space (Georgiou et al., 2021). However, evidence of mental health benefits of exposure to blue space is limited; anxiety-specific findings were particularly inconclusive, with negative (de Vries et al., 2016), positive (Generaal et al., 2019; White et al., 2021), and null associations reported previously (Gascon et al., 2018; Triguero-Mas et al., 2015).

4.1.3. Air pollution

We found linear associations in the expected direction between anxiety symptoms and $PM_{2.5}$, but the association did not reach significance. One possible explanation is that $PM_{2.5}$ effects may be more likely to be significant for more severe anxiety. Another Dutch study measured more severe anxiety using anxiolytics prescriptions and reported a significant positive association with $PM_{2.5}$ in both single and multiple exposure models, even after full covariate adjustments (Klompmaker et al., 2019). Supported through our RF results, another reason for the insignificant associations is that anxiety may be only positively associated with a higher level of $PM_{2.5}$.

As recent reviews suggested (Braithwaite et al., 2019; Lu, 2020), exposure to air pollution affects the risk of mental disorders by inducing oxidative stress and systemic inflammation (Arias-Perez et al., 2020), changing brain structure (Bernardi et al., 2021), and increasing stress hormone production (Li et al., 2017). However, anxiety-specific studies reported ambiguous $PM_{2.5}$ effects, with some showing null associations (Pelgrims et al., 2021; Shi et al., 2020; Vert et al., 2017).

4.1.4. Noise

Against our hypothesis, we found no significant linear anxiety-noise relationship. We speculate, supported by the RF models, that the association between noise and anxiety may be positive only for those exposed to pronounced noise levels of >60 dB. A similar nonlinear relationship between environmental noise and momentary annoyance was reported in China, with the threshold ranging from 58 dB to 78 dB (Zhang et al., 2020). Further, the association may reach significance with more severe anxiety, which would be congruent with meta-analytical evidence (Lan et al., 2020). Our noise variable combined various sources emitting noise, and each could have different effects. For example, road traffic noise was significantly associated with anxiety but was insignificantly related to railway noise in a previous Dutch study (Klompmaker et al., 2019).

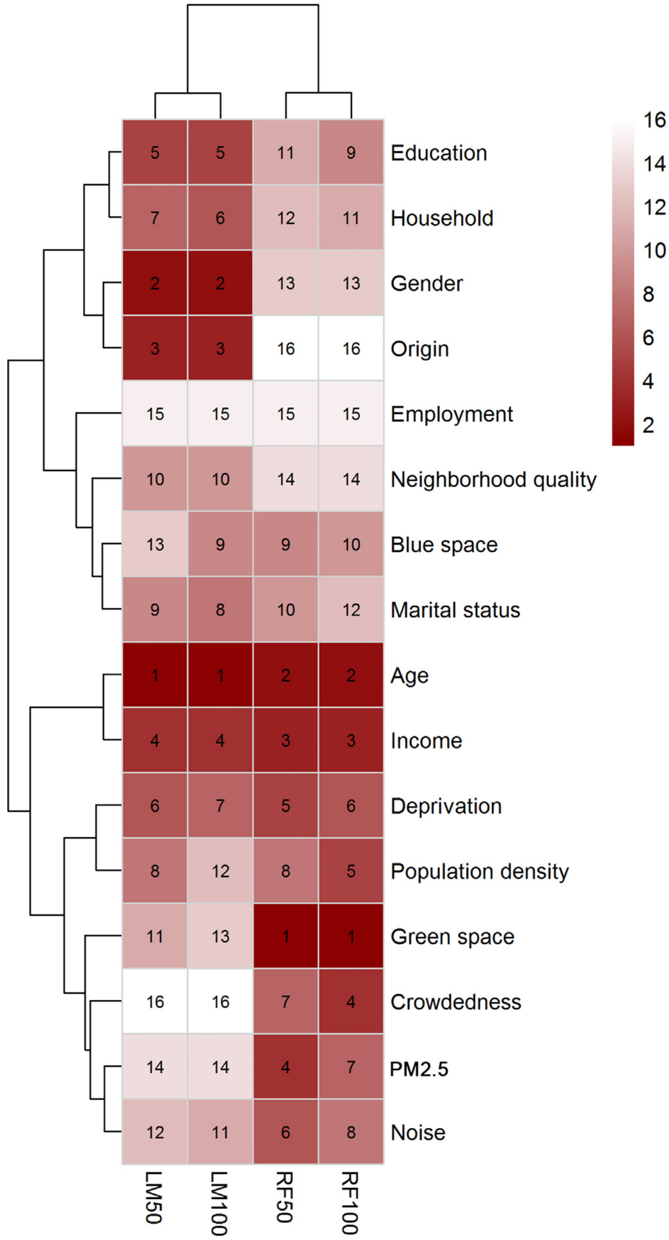

Fig. 4. Heat map showing the variable importance for linear regression model (LM) and random forest (RF) across buffer sizes (50 m and 100 m). The smaller the value the more important is a variable.

The underlying mechanisms for health-threatening noise exposure include an increase in physiological arousal and stress hormone secretion (Hahad et al., 2019) through stimulating the endocrine system and autonomic nervous system (Stansfeld and Clark, 2015). Reviews concluded that the available evidence of how noise affects mental health outcomes is inconclusive (Lan et al., 2020). As for anxiety, many studies also reported insignificant results (Okokon et al., 2018; Pelgrims et al., 2021; Zock et al., 2018).

4.1.5. Crowdedness

The positive association between crowdedness and anxiety also did not reach significance in our linear models. Participants with severe anxiety may withdraw from social situations and avoid crowded places during daily life. To the best of our knowledge, our study is the first to explore mobility-based crowdedness, making contextualization of our results difficult. The RF models revealed that the positive association between crowdedness and anxiety symptoms flattened out with pronounced crowdedness of >7.5. It is possible that those who could not tolerate high-density situations seek to leave while others stay and gradually adapt to the crowded occasion.

Crowded environments usually evoke negative emotions due to the invasion of personal space (Vine, 1982), which typically causes disliked social contact or interference and behavioral restrictions (Evans and Wener, 2007). Elsewhere crowded situations trigger aversive emotional responses of pedestrians (Engelniederhammer et al., 2019).

4.1.6. Potential interactions

Our RF models ranked environmental exposures as more crucial to explain GAD-7 scores. We speculate that RF captured interactions among environmental exposures, as stressed previously (Rugel and Brauer, 2020). For example, air pollution and noise may interact with each other because both are related to traffic and often co-occur spatiotemporally; green space can potentially reduce noise (Van Renterghem et al., 2015) and air pollutants (Nowak et al., 2014).

4.2. Strengths and limitations

We are not aware of any other study that assessed exposures along people's daily mobility paths on anxiety symptoms, taking the spatial co-occurrence of multiple exposures into account. Expanding prior studies (Roberts and Helbich, 2021), we went beyond the state-of-the-art by measuring the social environment dynamically in space-time using mobile phone-based Bluetooth sensing. While most studies examined linear dose-response exposure functions, we added to the literature by relaxing this overly simplistic assumption by means of machine learning, which is capable of modeling complex nonlinearities and variable interactions. Compared to ecological momentary assessments (Kirchner and Shiffman, 2016), which possibly affect participants' behavior by requiring them to fill in surveys several times per day, our study design likely reduced the Hawthorne effect (McCambridge et al., 2014) by letting the app run in the mobile phone's background. Prior tracking studies, many of which were only pilots within a single city, were constrained through small samples (Li et al., 2018). Ours was comparatively large and subjects were distributed across the Netherlands, which enabled different environmental settings.

Notwithstanding these strengths, some limitations must be acknowledged. Tracking data were only collected from Android devices, and although this represents roughly three-quarters of the market share (Kantar Worldpanel Comtech, 2019), specific population segments may have been excluded. Our anxiety assessment relied on a multiple-choice rating scale rather than clinical interviews, which is susceptible to self-reporting response bias. Bluetooth sensing is challenging; we cannot exclude that the mobile phones also captured signals from other devices (e.g., printers), which likely distorted the proxy measure of crowdedness. The $PM_{2.5}$ data captured the air pollution levels for 2009, which may not be entirely represent the situation in 2018 when the GPS data were collected. Travel patterns were not considered. Whether people's perception of the surrounding environment differs across travel modes warrants further research. Perceived exposures were disregarded, which were sometimes found to be more relevant for mental health outcomes than objective measures (Marquart et al., 2021). Environmental exposures may be associated with mental health through different indirect pathways (R. Zhang et al. 2021), which remained unaddressed. Future studies are encouraged to examine possible mediation effects. The Netherlands is a rather urbanized country, which may limit the transferability of our results to suburban or rural areas. As with virtually all mobile phone-based exposure studies (Chaix et al., 2013), our cross-sectional data prevented us from drawing conclusions about cause–effect relations; thus, reverse causation cannot be excluded.

5. Conclusion

In our mobile phone-based tracking study, we found null linear associations between anxiety symptoms and multiple environmental exposures (i.e., green space, blue space, noise, air pollution, and crowdedness) experienced along people's daily mobility paths. More importantly, the RF models not only indicated that the associations varied nonlinearly with the exposure levels, but also ranked the environmental exposures as more important for anxiety symptoms than linear models. We advise future studies also to assess non-linear associations which may only be inadequately captured through linear exposure models. Further GPS-based studies with longitudinal study designs are needed to support cause-effect statements between anxiety and environmental exposures over people's daily life rather than assessing exposures exclusively at the home address.

Ethics

The study was approved by the Ethics Committee at Utrecht University (FETC17–060). Survey data were enriched with registers. In line with Dutch privacy legislation, the register data are non-publicly accessible for scientific research in the secure environment of Statistics Netherlands.

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Data availability statement and code

The health data and mobile phone data (i.e., GPS, Bluetooth) are part of the NEEDS project and are non-publicly available due to privacy restrictions. Upon a reasonable request, data sharing agreements can be set up.

CRediT authorship contribution statement

YL: Conceptualization, Methodology, Formal analysis, Visualization, Writing - original draft, Funding acquisition.

HR: Data curation, Conceptualization, Methodology, Writing - review & editing.

MPK: Writing - review & editing, Supervision, Funding acquisition.

MH: Data curation, Conceptualization, Methodology, Writing - review & editing, Project administration, Funding acquisition, Supervision.

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2022.155276.

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