Full length article

Longitudinal associations of neighbourhood environmental exposures with mental health problems during adolescence: Findings from the TRAILS study

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A B S T R A C T

Background: Cross-sectional studies have found associations between neighbourhood environments and adolescent mental health, but the few longitudinal studies mainly focused on single exposure-based analyses and rarely assessed the mental health associations with environmental changes.

Objectives: We assessed longitudinal within- and between-person associations of multiple neighbourhood time-varying physical and social environmental exposures with externalising and internalising problems throughout adolescence.

Methods: We used four waves of TRAILS (Tracking Adolescents' Individual Lives Survey) data on self-reported externalising and internalising problems at ages 11, 13, 16, and 19 among 2,135 adolescents in the Netherlands. We measured residence-based time-varying environmental exposures, including green space, air pollution (fine particulate matter ($PM_{2.5}$)), noise, deprivation, and social fragmentation. We fitted random-effect within-between regression models to assess the environment-mental health associations.

Results: At the within-person level, an interquartile range (IQR) increase in $PM_{2.5}$ was associated with a 0.056 IQR (95% CI: 0.014, 0.099) increase in externalising problems, while an IQR social fragmentation increase was associated with a 0.010 IQR (95% CI: −0.020, −0.001) decrease in externalising problems. Stratification revealed that the association with $PM_{2.5}$ was significant only for movers, whereas the association with social fragmentation remained only for non-movers. At the between-person level, an IQR higher noise was associated with a 0.100 IQR (95% CI: 0.031, 0.169) more externalising problems, while higher deprivation ($\beta = 0.080$; 95% CI: 0.022, 0.138) and lower fragmentation (β = -0.073; 95% CI: −0.128, −0.018) were associated with more internalising problems. We also observed positive between-person associations between $PM_{2.5}$, noise, and internalising problems, but both associations were unstable due to the high $PM_{2.5}$-noise correlation. Further, we observed a non-linear between-person $PM_{2.5}$-externalising problems association turning positive when $PM_{2.5} > 15$ μg/m³. Null associations were found for green space.

Conclusion: Our findings suggested that air pollution, noise, and neighbourhood deprivation are risk factors for adolescent mental health. Not only exposure levels but also exposure changes matter for adolescent mental health.

1. Introduction

Globally, mental health problems among adolescents are a matter of concern, as approximately 20% of adolescents suffer from such problems (WHO, 2020). In addition to the individual- and family-level factors, adolescent mental health may also be related to the environmental conditions of the residential neighbourhood (Fleckney & Bentley, 2021). Adolescents are thought to be highly susceptible to residence-based environmental exposures since they spend considerable parts of their daily lives in the residential neighbourhood due to limited autonomy and mobility (Allison et al., 1999; Visser et al., 2021). Furthermore, adolescents' immature brains and neurocognitive functioning, critical

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for mental health development, may be susceptible to several environmental stressors (Calderón-Garcidueñas et al., 2014; Zare Sakhvidi et al., 2018).

Studies investigating environment-mental health associations among adolescents are predominantly cross-sectional (Fleckney & Bentley, 2021; Visser et al., 2021). The limited longitudinal evidence suggests that more green space (Bloemsma et al., 2022; Maes et al., 2021; Van Aart et al., 2018; Younan et al., 2016), less air pollution (Bloemsma et al., 2022; Karamanos et al., 2021; Reuben et al., 2021; Roberts et al., 2019; Shen et al., 2021; Younan et al., 2018), and lower neighbourhood deprivation (Jonsson et al., 2018; King et al., 2022), are beneficial to adolescent mental health. By contrast, the harmful effects of noise and social fragmentation on adolescent mental health, reported in some cross-sectional studies (Bao et al., 2022; Dzhambov et al., 2017; Fagg et al., 2008), has rarely been confirmed longitudinally (Bloemsma et al., 2022; Clark et al., 2013; Goldstein et al., 2019; Tangermann et al., 2022).

While advanced in the methodological designs, several limitations have remained in prior longitudinal studies. First, within-person associations have rarely been distinguished from between-person associations. Between-person associations compare the mental health of individuals with different exposure levels, reflecting whether adolescents with higher exposure levels exhibit better or worse mental health than those with lower exposure levels. Within-person associations compare the same persons with changing exposures over time, revealing whether exposure changes are associated with mental health changes. Within-person associations can differ markedly from between-person associations in both effect sizes and directions (Hamaker & Muthén, 2020). Most studies, however, implicitly assumed equivalence between them, resulting in a mixture of both types of associations that may be difficult to interpret (Bloemsma et al., 2022; Goldstein et al., 2019; Maes et al., 2021).

Second, most studies only used environmental measurements at a single point in time and implicitly assumed that adolescents' residential environments could only be changed by residential relocation (Jonsson et al., 2018; Tangermann et al., 2022). Non-movers, however, may also experience changes in some environmental exposures, such as air pollution (Statistics Netherlands, 2023a) and social fragmentation (Feijten & Van Ham, 2009; Van Ham & Clark, 2009), possibly due to evolution in urban spaces, and changes in population composition driven by population turnover within neighbourhoods (Pearce et al., 2018). Time-varying environmental measurements are therefore needed to capture adolescents' actual environmental exposures over time.

Third, most studies ignored spatial co-exposure and investigated exposures in isolation (Fleckney & Bentley, 2021). For example, air pollutants and noise were found to be concentrated in areas with less green space (Markevych et al., 2017), and higher deprivation (Casey et al., 2017; Hajat et al., 2021). Studies ignoring the interplay among exposures are prone to omitted confounding bias and may therefore overestimate the mental health-effect of a single exposure.

To respond to these knowledge gaps, we aimed to assess the joint associations of multiple time-varying neighbourhood physical and social environmental exposures with mental health problems at both the between- and within-person levels throughout adolescence. We focused on externalising and internalising problems, two broad, distinctive, and well-established dimensions of adolescent mental health problems (Achenbach, 1966). Specifically, externalising problems cover outer-directed problems such as aggression and delinquency, whereas internalising problems are more inner-directed, referring to problems including depression and anxiety (Achenbach & McConaughy, 1997). Two hypotheses were tested; first, at the between-person level, adolescents exposed to higher levels of green space, lower levels of air pollution, noise, neighbourhood deprivation, and social fragmentation showed fewer externalising and internalising problems. Second, at the within-person level, adolescents with increased exposure to green space, decreased exposure to air pollution, noise, neighbourhood deprivation, and social fragmentation showed decreased externalising and internalising problems.

2. Materials and methods

2.1. Study population

Data were obtained from TRAILS (Tracking Adolescents' Individual Lives Survey), a prospective study conducted in the north of the Netherlands. We used a population-based cohort that included 2,229 adolescents born between 1st October 1989 and 30th September 1991. Respondents were asked to complete questionnaires every two or three years from early adolescence to early adulthood. We used the first four survey waves conducted when respondents were 11, 13, 16, and 19 years old (T_1: March 2001-July 2002, T_2: September 2003-December 2004, T_3: September 2005-August 2007, T_4: October 2008-September 2010). Retention rates of respondents over the four waves were 81.4%-96.4%. An in-depth study description can be found elsewhere (Oldehinkel et al., 2015). All adolescents and parents provided written informed consent. Ethical approval was obtained from the Dutch Central Committee on Research Involving Human Subjects (#NL38237.042.11).

2.2. Outcomes

We measured self-reported adolescent externalising and internalising problems using the Youth Self Report (YSR) from T_1 to T_3 and the Adult Self Report (ASR) in T_4. A three-point Likert scale (not true, somewhat or sometimes true, and very or often true) was used to generate responses. While the YSR is typically used for children and young adolescents, some items are replaced with alternatives suitable for older adolescents and young adults in the ASR (Achenbach & Rescorla, 2001, 2003). The aggregated score of externalising problems was calculated using 32 YSR items or 35 ASR items on the *Aggressive* and *Delinquent Behaviours* subscales. Internalising problems were assessed using 31 YSR items or 39 ASR items on the *Withdrawn/Depressed*, *Anxious/Depressed*, and *Somatic Complaints* subscales. Higher scores indicate more externalising or internalising problems.

2.3. Time-varying environmental exposures

Green space was measured using annual satellite-based Normalized Difference Vegetation Index (NDVI) data at a 30 × 30 m resolution (Tucker, 1979). We derived the remote sensing scenes from Landsat5 and Landsat7 in the Google Earth Engine. The NDVI represents green biomass levels based on land surface reflectance of visible red and near-infrared radiation. Due to seasonal vegetation cycles, cloud-free images collected during the 2001–2010 growing seasons (i.e., May-September) were used to match the year of each survey wave. NDVI values range from −1 to 1. Pixels with negative values (water bodies) were masked, leaving positive ones with higher values indicating greater green coverage.

Air pollution was measured using yearly concentration estimates (μg/m^3) of fine particulate matter with < 2.5 μm in diameter (PM$_{2.5}$) during 2001–2010. Ground-level PM$_{2.5}$ estimates with a 1 × 1 km resolution were derived from the European Regional Estimates (V4.EU.03; Van Donkelaar et al., 2019). This data product extended the methodology used for North America (V4.NA.02) to the European context (Van Donkelaar et al., 2019). Briefly, estimates of ground-level PM$_{2.5}$ concentrations were derived based on satellite data from multiple sources combined with chemical transport models and calibrated with European ground-based PM$_{2.5}$ measurements using geographically weighted regression (Van Donkelaar et al., 2019). Modelling details are given elsewhere (Hammer et al., 2020; Van Donkelaar et al., 2019).

Noise data captures daily average noise emissions (Lden) from the road-, rail-, and air traffic. The emissions were estimated by the Netherlands Environmental Assessment Agency (PBL) using the Empara

Noisetool with a 25 × 25 m resolution (PBL, 2008). The model accounts for numerous factors such as road traffic intensity, heavy traffic, pavement type, noise barriers, train equipment, type of flights, and rail and flight timetables. Noise level assessments were expressed in decibels (dB (A)) during the day (7–19 h), evening (19–23 h), and night (23–7 h). A 5 and 10 dB penalty was respectively added on the evening and night-time noise level. Survey waves were matched with the most temporally proximate noise data from 2000, 2004, 2007, and 2010.

Neighbourhood deprivation was operationalised using administrative register data for neighbourhood-based residents in all addresses across the Netherlands on January 1st of each survey year. Given that input data were only available since 2005, the missing years from 2001 to 2004 were back casted via best-fitting neighbourhood-based autoregressive integrated moving average models or exponential smoothing models using data from 2005 to 2016. Our composite measure included the reversely coded standardised median household income, the unemployment rate, and the proportion of households below the poverty line (Hagedoorn et al., 2020). These variables were z-scored yearly and summed to obtain a total deprivation score. Higher scores represent more deprivation.

Social fragmentation represents neighbourhood social disconnection, disorganisation, and resident instability. We measured this indicator by summing yearly z-scores for the proportion of unmarried adults, single-household residents, and moved-in residents in the previous year based on all yearly addresses across the Netherlands (Congdon, 2011; Hagedoorn et al., 2020). Similarly, data were extracted from population-wide registers on January 1st of each survey year. Missing years during 2001–2004 were back casted as above. Higher scores indicate more social fragmentation.

We used the four-digit postal code (PC4) areas as a proxy of residential neighbourhoods. We aggregated each exposure per neighbourhood and assigned the exposure values to the respondents on the date of the survey wave. Specifically, we calculated the average pixel values within each neighbourhood for green space, air pollution, and noise, while deprivation and social fragmentation were calculated by aggregating linked register data geocoded on the address level per neighbourhood. Respondents lived in 334 neighbourhoods over all waves, with a median size of 3.44 km^2 and an interquartile range (IQR) of 7.18 km^2.

2.4. Covariates

We adjusted a *priori* for several time-invariant covariates at baseline, including sex (male or female), ethnicity (native or non-native), family socioeconomic status (high, intermediate, or low), divorce of biological parents (yes or no), the number of parents at home (one or two), and the history of parental externalising and internalising problems (continuous), and two time-varying covariates, including adolescents' education levels represented by four education tracks (lower vocational and special education track, intermediate educational track, higher vocational track, academic track, and missing; Schmengler et al., 2021), and the survey waves treated as dummy variables to control for fixed time effects.

3. Statistical analyses

Descriptive statistics summarised the data across waves. We used Spearman correlation coefficients (r_s) to assess the bivariate associations between exposures.

We fitted random-effect within-between regression models to assess longitudinal associations of environmental exposures with externalising and internalising problems at the within- and between-person level (Bell et al., 2019). Estimates at the within-person level are robust to unobserved time-invariant confounders, while the multilevel structure allows for estimates at the between-person level (Bell et al., 2019). To separate the level-specific estimation, time-varying exposures and covariates

were split into person-specific means (i.e., between-person component) and deviations from the means (i.e., within-person component). For time-varying categorical covariates (i.e., the education level and waves), each dummy-coded variable was split using the same dividing process as for the continuous covariates (Yaremych et al., 2021).

We calculated the Intraclass Correlation Coefficients (ICCs) of time-varying exposures and outcomes to quantify the relative amount of within- and between-person variance. We included the person-level random intercepts to control for clusterings of repeated measures within individuals. We disregarded the neighbourhood-level random intercepts for model parsimony, given a neglectable amount of clustering within neighbourhoods (ICCs < 0.01). Our model was given as:

$$y_{it} = \beta_0 + \beta_w(x_{it} - \overline{x_i}) + \beta_b\overline{x_i} + \beta Z_i + \mu_i + \varepsilon_{it}$$

where y_{it} represents the score of externalising or internalising problems for person i at wave t. Each time-varying exposure and covariate x_{it} had a within-person component ($x_{it} - \overline{x_i}$) and between-person component $\overline{x_i}$ with the estimate of the within-person effect β_w and between-person effect β_b. Z_i represents each time-invariant covariate with the effect estimate of β. μ_i and ε_{it} indicate the random effect for person i and the residuals, respectively.

We fitted several models with full covariate-adjustment. Model 1 included each exposure separately, while Model 2 jointly included all exposures (the largest value of the variance inflation factor = 2.9). To facilitate the interpretation of the effect sizes, we reported the effect estimates as the IQR-unit difference in the outcome per IQR increment/ higher of the within/between-person component of each exposure. We reported the 95% confidence intervals (CIs) based on cluster-robust sandwich standard errors. All analyses were performed in R, version 4.1.2, with the *lmer4* (Bates et al., 2022) and *clubSandwich* packages (Pustejovsky, 2018).

We conducted several sensitivity analyses to examine the robustness of the results. First, we stratified the sample into movers and non-movers for two reasons: 1) although movers and non-movers can both experience exposure changes, we expected more exposure changes before and after residential relocation possibly leading to more pronounced within-person associations; 2) compared to the within-person associations, the between-person associations are more prone to selective migration bias. We minimalised such bias due to selective moving in the estimation of between-person associations by excluding movers from the sample. We, therefore, interpreted the between-person association only for non-movers. In practice, for movers ($N = 823$), we used observations from the waves before and after moving. For non-movers ($N = 2,124$), we included observations from all waves for respondents who have not relocated, as well as observations from the waves until relocation for respondents with moving history across waves. Second, we adjusted for urbanicity as a proxy of urban factors that might confound our exposure-outcome associations in Model 1. Time-varying urbanicity values were captured by calculating each neighbourhood's annual address density per km^2. Further, due to the high correlations between urbanicity and exposures, we dichotomised urbanicity into urban ($\geq$ 1,000 addresses/ km^2) and rural areas (< 1,000 addresses/km^2; Statistics Netherlands, 2023b), and controlled for this dichotomised variable in Model 1 given the moderate correlations between exposures and the dichotomised variable of urbanicity (point-biserial correlations = ±0.38–0.60). Third, given possible non-linear exposure-outcome associations, we fitted generalised additive models where all linear exposure terms were replaced with thin-plate splines (Wood, 2006). Finally, since residential relocation might lead to both environmental and mental health changes, we conducted two additional analyses to mitigate the possible confounding effect of relocation. 1) We controlled for participants' moving history since the previous survey wave (movers or non-movers (non-movers served as the reference category)) as a dummy variable in both Model 1 and 2; 2) we refitted Model 1 and 2 in the sample without observations from wave 4 when some participants (31%) moved out

from parents' home and started living independently.

4. Results

4.1. Descriptive statistics

Our analytical sample consisted of 2,135 adolescents participating in at least one survey wave. We excluded respondents with missing data for outcomes ($N = 4$), home location ($N = 19$), and covariates ($N = 71$) (Figure S1).

Table 1
Study population characteristics and environmental exposures across waves.

Variable	N (%) or mean (standard deviation)			
	Wave 1 (N = 2,074)	Wave 2 (N = 1,983)	Wave 3 (N = 1,575)	Wave 4 (N = 1,616)
Outcomes				
Internalising problems	0.36 (0.24)	0.33 (0.24)	0.31 (0.25)	0.25 (0.24)
Externalising problems	0.27 (0.20)	0.29 (0.20)	0.31 (0.21)	0.23 (0.21)
Demographics				
Age	11.11	13.56	16.24	19.04
	(0.55)	(0.52)	(0.68)	(0.58)
Sex at birth				
Female	1,063	1,022	844	887
	(51.3%)	(51.5%)	(53.6%)	(54.9%)
Male	1,011	961	731	729
	(48.7%)	(48.5%)	(46.4%)	(45.1%)
Ethnicity				
Native	1,857	1,793	1,451	1,493
	(89.5%)	(90.4%)	(92.1%)	(92.4%)
Foreigner	217	190 (9.6%)	124 (7.9%)	123 (7.6%)
	(10.5%)			
Education level				
Lower vocational &	586	566	386	260
special education	(28.3%)	(28.5%)	(24.5%)	(16.1%)
Intermediate	494	476	418	513
vocational	(23.8%)	(24.0%)	(26.5%)	(31.7%)
Higher vocational	409	404	356	462
	(19.7%)	(20.4%)	(22.6%)	(28.6%)
Academic	455	448	402	356
	(21.9%)	(22.6%)	(25.5%)	(22.0%)
Missing	130 (6.3%)	89 (4.5%)	13 (0.8%)	25 (1.5%)
Family socioeconomic status				
Low	518	486	342	335
	(25.0%)	(24.5%)	(21.7%)	(20.7%)
Mid	1,030	989	774	817
	(49.7%)	(49.9%)	(49.1%)	(50.6%)
High	526	508	459	464
	(25.4%)	(25.6%)	(29.1%)	(28.7%)
(Biological) Parental divorce				
Not divorced	1,640	1,568	1,263	1,308
	(79.1%)	(79.1%)	(80.2%)	(80.9%)
Divorced	434	415	312	308
	(20.9%)	(20.9%)	(19.8%)	(19.1%)
Parents numbers				
One parent	317	293	221	216
	(15.3%)	(14.8%)	(14.0%)	(13.4%)
Two parents	1,757	1,690	1,354	1,400
	(84.7%)	(85.2%)	(86.0%)	(86.6%)
Parental internalising problems	0.55 (0.80)	0.55 (0.80)	0.54 (0.78)	0.54 (0.79)
Parental externalising problems	0.14 (0.42)	0.14 (0.42)	0.13 (0.39)	0.13 (0.39)
Environmental exposures				
Green space	0.45 (0.09)	0.41 (0.11)	0.46 (0.10)	0.44 (0.11)
$PM_{2.5}$ (µg/m^3)	12.93	14.30	13.46	13.02
	(1.20)	(0.77)	(1.38)	(1.91)
Noise (dB(A))	51.25	51.28	51.46	52.87
	(4.37)	(4.59)	(4.65)	(4.65)
Deprivation	2.24 (2.66)	2.04 (2.51)	1.69 (2.33)	1.87 (2.28)
Social fragmentation	1.97 (2.80)	1.88 (2.84)	1.62 (2.88)	3.50 (3.93)

Table 1 summarises the sample characteristics and exposure distribution across the waves. On average, internalising problems decreased steadily over time, while externalizing problems showed an upward trend from T_1 to T_3, followed by a sharp decline in T_4. Respondents were roughly equally distributed across sex (48.7% were male at baseline). Almost half of the adolescents lived in families with intermediate socioeconomic levels (49.7% at baseline). Most of them were native (89.5% at baseline), had not experienced parental divorce (79.1% at baseline), and lived with two parents at home (84.7% at baseline). The exposure levels for green space, noise, and deprivation remained, on average, relatively stable over waves. We observed some temporal fluctuations for the average levels of $PM_{2.5}$ and social fragmentation. In particular, the average social fragmentation level increased dramatically from wave 3 (1.62 ± 2.88) to 4 (3.50 ± 3.93), during which more residential relocation occurred.

4.2. ICCs and correlations among exposures

Table S1 depicts the ICCs for the exposures. ICCs for green space, noise and deprivation are 0.675, 0.727, and 0.731, indicating that the variance of these exposures were primarily due to the between-person differences (67.5%-73.1%), with a minority due to the within-person changes (26.9%–32.5%). An opposite pattern was found for $PM_{2.5}$ (ICC: 0.247), showing a smaller between-person variance (24.7%) compared to the within-person variance. A more evenly distributed variance was found in social fragmentation (ICC: 0.539).

Figure S2 depicts the correlations between the exposures. At the between-person level, $PM_{2.5}$ and noise were positively correlated (r_s = 0.68), and both were negatively correlated with green space ($r_s = -0.78$ and -0.65). We observed strong positive between-person correlations between social fragmentation and deprivation ($r_s = 0.64$). Social fragmentation and deprivation were positively correlated with $PM_{2.5}$ and noise, and negatively correlated with green space at the between-person level. These correlations were moderate for social fragmentation (r_s = 0.46, 0.41, and -0.50) and weak for deprivation ($r_s = 0.22, 0.14$, and -0.20). All within-person correlations showed the same direction as those at the between-person level, but overall, magnitudes were weaker. Exposures across between- and within-person levels were uncorrelated.

4.3. Results of main analyses

Fig. 1 depicts the regression results. Full numeric results are provided in Tables S2 and S3. At the within-person level, green space changes were not associated with changes in either externalising or internalising problems. At the between-person level, green space was negatively associated with externalising problems (Model 1), but this association disappeared after co-exposure adjustments (Model 2). We observed null between-person green space-internalising problems associations.

At the within-person level, an IQR increase in $PM_{2.5}$ was associated with a 0.056 IQR (95% CI: 0.014, 0.099) increase in externalising problems (Model 2). We observed null within-person associations between $PM_{2.5}$ changes and changes in internalising problems. At the between-person level, the positive association between $PM_{2.5}$ and externalising problems observed in Model 1 was fully attenuated to null after co-exposure adjustments (Model 2). We also observed a positive between-person $PM_{2.5}$-internalising problems association with a similar strength in Model 1 and Model 2. However, compared to the results of Model 1, the confidence interval of this association ($\beta_b = 0.075$; 95% CI: $-0.009, 0.158$) became wider in Model 2, possibly due to the high correlations among physical exposures at the between-person level ($r_s = \pm 0.65$–0.78).

We did not observe within-person associations of noise changes with changes in either externalising or internalising problems. At the between-person level, an IQR higher noise level was associated with a 0.100 IQR (95% CI: 0.031, 0.169) higher level of externalising problems (Model 2). We also observed a positive between-person noise-
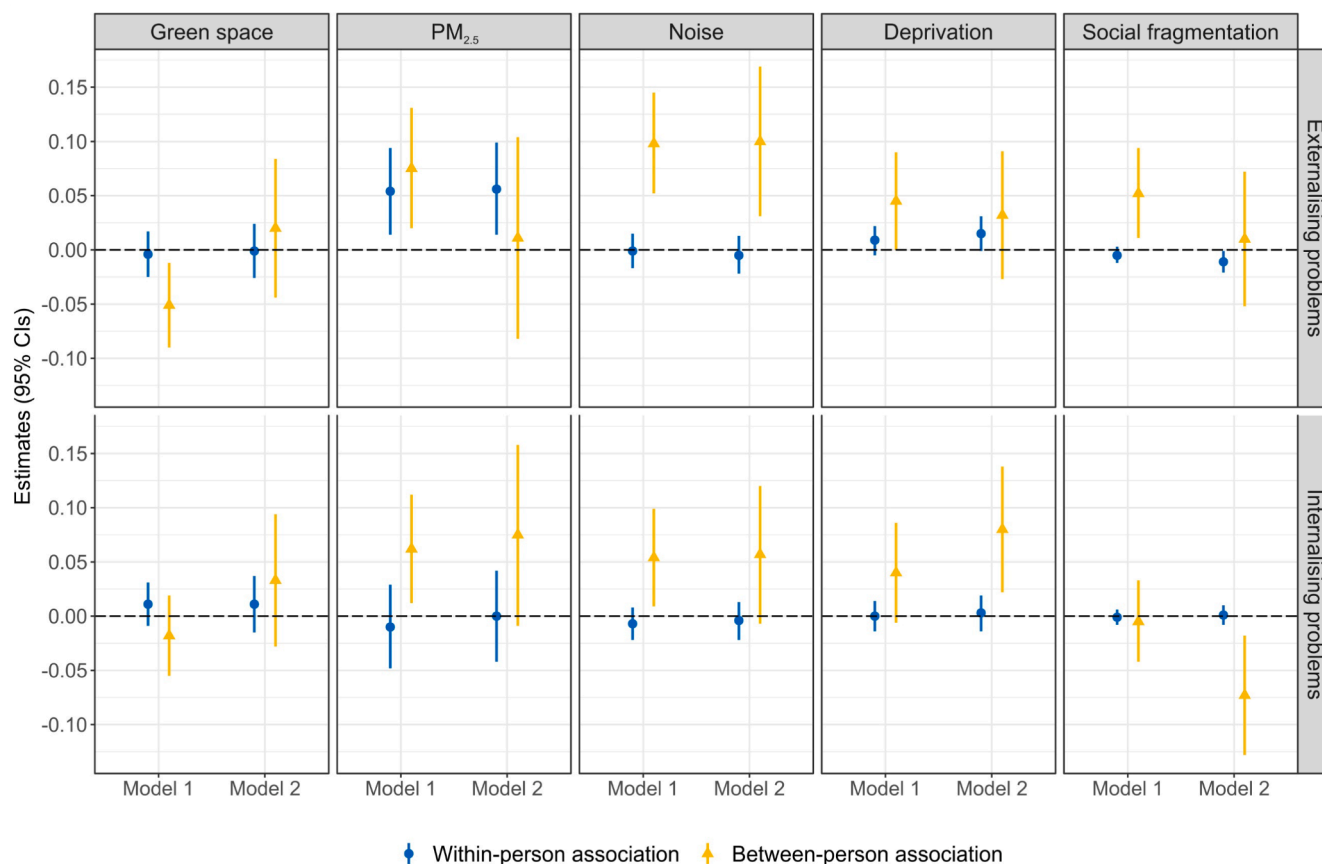
Fig. 1. Within-person and between-person associations of green space, PM$_{2.5}$, noise, deprivation, and social fragmentation with adolescent externalising and internalising problems. The effect sizes estimates (y-axis) represent the IQR-unit differences in externalising or internalising problems associated with an IQR increment/higher of the within/between-person component of each exposure. Points and error bars represent point estimates and 95% CI, respectively. The effect estimates were obtained from the random-effect within-between regression models. Model 1 was adjusted for sex, ethnicity, family socioeconomic status, divorce of biological parents, the number of parents, history of parental externalising and internalising problems, adolescents' education level, and the waves. Model 2 additionally adjusted for co-exposures. Note: IQR values of the within- and between-person component of green space are 0.04 and 0.11; of PM$_{2.5}$ are 1.53 and 1.55; of noise are 1.27 and 6.03; of deprivation are 0.61 and 3.03; of social fragmentation are 0.53, 3.26; of externalising problems are 0.15 and 0.21; of internalising problems are 0.18 and 0.26. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

internalising problems association in Model 1. Controlling for multi-exposures did not markedly change the strength of this association (β_b = 0.057; 95% CI: −0.007, 0.120). Still, the confidence interval became wider given pronounced correlations among physical exposures (Model 2).

We found null within-person associations between deprivation changes and changes in externalising and internalising problems. At the between-person level, an IQR higher deprivation level was associated with a 0.080 IQR (95% CI: 0.022, 0.138) higher level of internalising problems (Model 2). We also observed a positive between-person deprivation-externalising problems association (Model 1), which disappeared after controlling for co-exposures (Model 2).

At the within-person level, an IQR social fragmentation increase was associated with a 0.010 IQR (95% CI: −0.020, −0.001) decrease in externalising problems (Model 2). We observed null within-person associations between social fragmentation changes and changes in internalising problems. At the between-person level, an IQR higher social fragmentation level was associated with a 0.073 IQR (95% CI: −0.128, −0.018) lower level of internalising problems. We also observed a positive between-person social fragmentation-externalising problems association in Model 1, which was fully attenuated in Model 2 with co-exposure adjustments.

4.4. Results of a post-hoc analysis

Due to the strong correlations among the between-person components of physical exposures, we did a post-hoc analysis by modelling green space, PM$_{2.5}$, and noise separately, while controlling for the social environmental exposures (i.e., deprivation and social fragmentation) and all individual- and family-level covariates (Model 1a). The model results (Table 2) indicated significant positive between-person associations between PM$_{2.5}$, noise, and internalising problems. Further, these two associations remained significant (PM$_{2.5}$: (β_b = 0.098; 95% CI:

Table 2
Results of three models (Model 1a) with green space, air pollution, and noise separately included.

Exposure (IQR)	Externalising problems β (95% CI)	Internalising problems β (95% CI)
β_w Green space (0.04)	−0.011 (−0.035, 0.012)	0.013 (−0.011, 0.037)
β_b Green space (0.11)	−0.037 (−0.082, 0.008)	−0.036 (−0.081, 0.008)
β_w PM$_{2.5}$ (1.53)	0.054 (0.014, 0.095)	−0.010 (−0.050, 0.030)
β_b PM$_{2.5}$ (1.55)	0.060 (−0.002, 0.123)	0.086 (0.028, 0.142)
β_w Noise (1.27)	0.002 (−0.015, 0.018)	−0.007 (−0.024, 0.009)
β_b Noise (6.03)	0.094 (0.042, 0.145)	0.076 (0.028, 0.125)

Note: β_w: within-person estimate; β_b: between-person estimate. All models controlled for deprivation, social fragmentation, and all individual- and family-level covariates.

0.022, 0.175); Noise: ($\beta_b = 0.078$; 95% CI: 0.020, 0.137)) when we additionally controlled for green space in Model 1a (results are not shown). These two associations were also found significant in Model 1, but they turned insignificant with wider confidence intervals in Model 2 (main analyses). Other significant associations found in the post-hoc analysis aligned with the results of Model 2.

4.5. Results of sensitivity analyses

The sensitivity analyses confirmed the robustness of the between-person association between noise and externalising problems and the between-person association between deprivation, social fragmentation, and internalising problems. The other associations reported in the main analyses were not robust. First, at the within-person level, only movers with increased $PM_{2.5}$ showed increased externalising problems, whereas only non-movers with increased social fragmentation showed decreased externalising problems (Table S4). Second, compared to the results of Model 1, adjusting for urbanicity attenuated the between-person green space-externalising problems association, $PM_{2.5}$-externalising problems association, and social fragmentation-externalising problems association to insignificant. These associations were also found insignificant in the results of Model 2 and the post-hoc analysis (Table S5). Third, all linear associations that we found in the main analysis were confirmed as linear (Figs. 2-3), while an additional non-linear between-person $PM_{2.5}$-externalising problems association was found, showing that $PM_{2.5}$ was positively associated with externalising problems only for adolescents with $PM_{2.5}$ concentrations above approximately 15 µg/m³ (Fig. 2). However, the confidence intervals of the spline were somewhat wider

due to relatively fewer observations above 15 µg/m³. Finally, associations observed in Model 1 and 2 remained stable when controlling for the moving history since the previous survey wave (Table S6). Since residential relocations mostly occurred between wave 3 and 4, refitting Model 2 without wave 4 observations led to similar results to the model for the non-movers sample (Table S7).

5. Discussion

5.1. Main findings

This is the first study investigating longitudinal within- and between-person associations of multiple neighbourhood environmental exposures with externalising and internalising problems throughout adolescence. Our results show that at the within-person level, adolescents exposed to increased air pollution and decreased social fragmentation showed increased externalising problems. The association with air pollution was robust only for movers, whereas the association with social fragmentation only applied to non-movers. At the between-person level, adolescents exposed to higher noise levels showed more externalising problems, while higher deprivation levels and lower social fragmentation levels were associated with more internalising problems. We also observed positive between-person associations of air pollution and noise with internalising problems, although the results were less stable due to a strong correlation between these two exposures. Furthermore, we found a non-linear between-person air pollution-externalising problems association, which turned positive when $PM_{2.5}$ concentration was > 15 µg/m³.
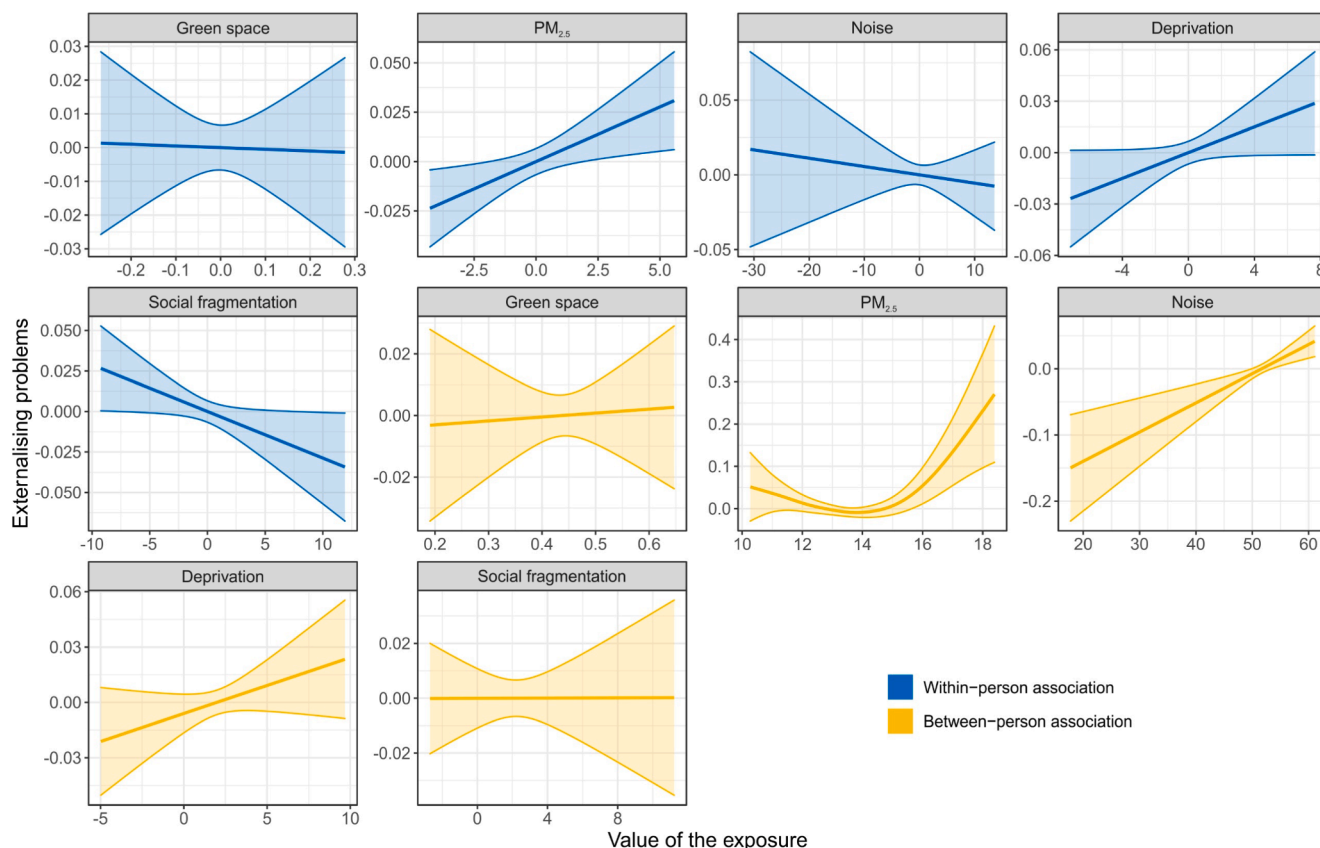
Fig. 2. Non-linear within- and between-person associations between each exposure and externalising problems. The model controlled for all covariates and co-exposures. Smooth functions were added to the within- and between-person components of all exposures in the same model. The smoother was implemented as a thin plate spline to circumvent an overly constrained or wiggly expose-response function. The effective degrees of freedom (EDF) reflect the level of non-linearity. With an EDF of 3.589, there was a clear indication of a non-linear shape in the between-person association between $PM_{2.5}$ and externalising problems. Other exposure-outcome associations show EDF of 1 indicating linear shapes. Shaded regions indicate 95% CIs.
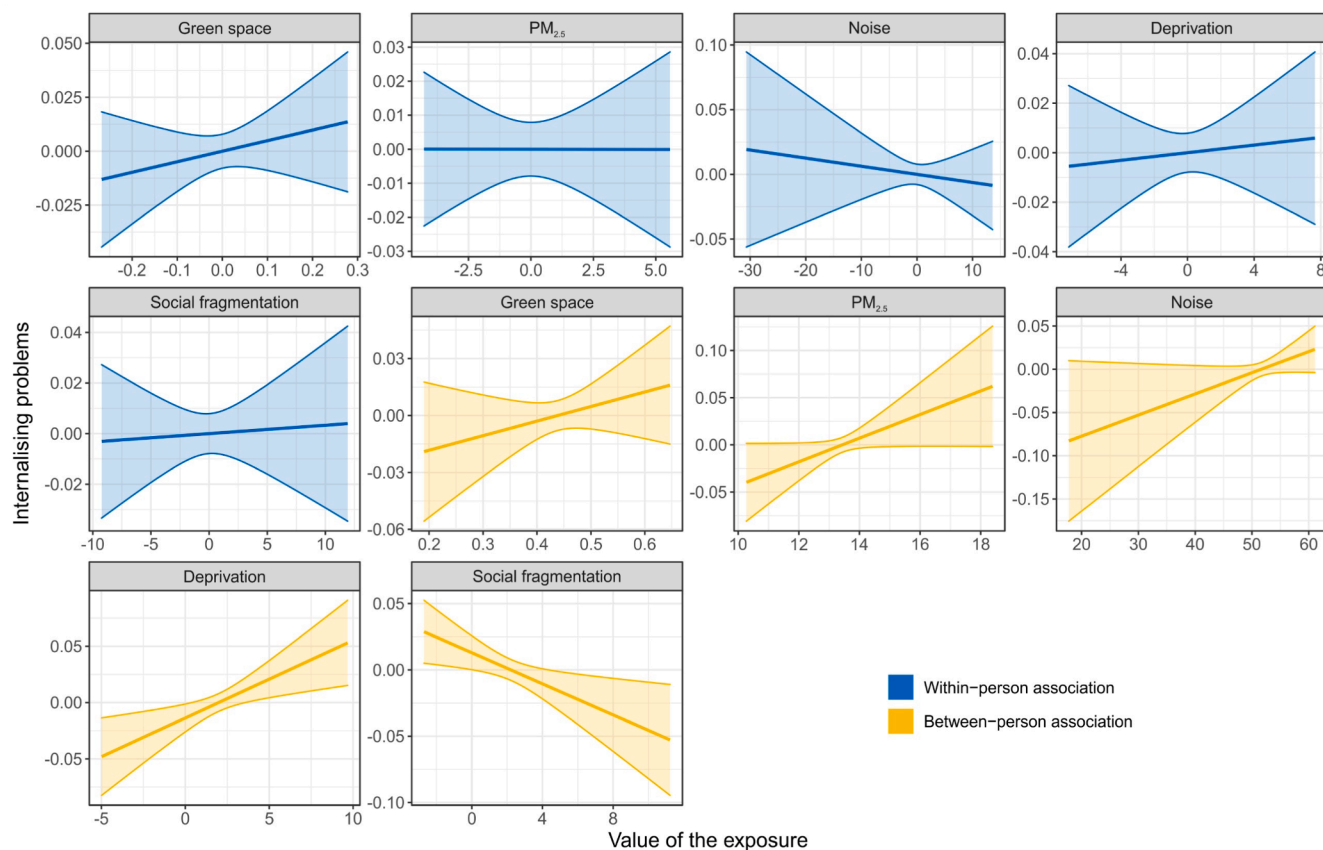
Fig. 3. Non-linear within- and between-person associations between each exposure and internalising problems. The model controlled for all covariates and co-exposures. Smooth functions were added to the within- and between-person components of all exposures in the same model. The smoother was implemented as a thin plate spline to circumvent an overly constrained or wiggly expose-response function. The effective degrees of freedom (EDF) reflect the level of non-linearity. All exposure-outcome associations show EDF of 1 indicating linear shapes. Shaded regions indicate 95% CIs.

5.2. Interpretation of findings

We found that adolescents exposed to increased air pollution showed increased externalising problems. Potential biological mechanisms for this linkage include increased oxidative stress, dopaminergic neuronal damage, and neuroinflammation (Allen et al., 2014; Calderón-Garcidueñas et al., 2014). We are unaware of other studies assessing the within-person associations between air pollution changes and adolescent mental health changes with which to compare our findings. We also found that after stratification, the positive association of air pollution changes remained significant only for movers. One possible reason for this finding is that air pollution changes are larger and more perceptible for movers than non-movers. Alternatively, the cumulative fatigue hypothesis suggests that people may have a reduced capacity to cope with environmental stressors when confronted with other life stressors (Cohen et al., 2013). Movers may be more vulnerable to increased air pollution since they may be less able to cope with the combined effects of worsening air pollution and adverse effects caused by moving-related stressors such as disconnection from previous social networks.

Furthermore, we found a threshold effect of air pollution at the between-person level, implying that the hazardous effect of $PM_{2.5}$ on externalising problems may appear when the concentration exceeds 15 $\mu g/m^3$. A similar threshold effect of air pollution was found in a UK study, indicating that adolescents with $PM_{2.5} > 12.4$ $\mu g/m^3$ reported more psychotic experiences (Newbury et al., 2019). The threshold observed in our study is well below the 25 $\mu g/m^3$ annual limit set for general population use in the European Union's air quality guidelines, possibly supporting the assumption of the higher vulnerability of adolescents.

Our results also indicated that adolescents exposed to higher noise levels showed more externalising problems, whereas a less stable positive between-person association was found between noise and internalising problems. These results aligned with earlier studies (Bao et al., 2022; Forns et al., 2016; Haines et al., 2001). A possible explanation is that noise could raise arousal and physiological activity levels, potentially provoking more externalising rather than internalising problems (Bao et al., 2022; Cohen et al., 2013; Forns et al., 2016; Haines et al., 2001).

For air pollution and noise, we observed significant associations with internalising problems at the between-person level. However, due to the high air pollution-noise correlation, both associations became insignificant when both exposures were included in the same model. Therefore, the mutual confounding between these two exposures is hard to be mitigated in our analyses, which impedes the separation of the independent associations between air pollution, noise and internalising problems, and thus, the results need to be interpreted with care.

In line with prior evidence (Huang et al., 2020; King et al., 2022), we found that higher deprivation levels were associated with more internalising problems. One explanation is that more deprived neighbourhoods are characterised by the limited resources and facilities (Leventhal & Brooks-Gunn, 2000; Visser et al., 2021), and the competition for scarce resources may impose adolescents to a stressful living condition and lead to internalising problems (Leventhal & Brooks-Gunn, 2000). Furthermore, violence and social disorders tend to be more common in deprived neighbourhoods (Galster, 2012; Leventhal & Brooks-Gunn, 2000). Adolescents exposed to violence as witnesses or victims may feel insecure, thus experiencing more stress and exacerbating internalising problems (Galster, 2012; Leventhal & Brooks-Gunn,

2000).

By contrast with our expectations, we found a negative between-person social fragmentation-internalising problems association, which was confirmed in the analysis for the non-movers sample. We also found that non-movers with decreased social fragmentation showed increased externalising problems, but the effect size was minor and only marginally significant. A possible explanation for both associations is that social fragmentation scores are shaped by demographic characteristics including unmarried adults and new moved-in residents in the neighbourhood, and lower or decreases in this social fragmentation indicator may be driven by less inflow of residents and increased losses of young adults (unmarried), which is typical in the northern Netherlands, where employment opportunities and educational resources are limited. Increased social problems caused by population loss, such as vacancies, disinvestment, and social instabilities, may therefore lead to more externalising and internalising problems among local adolescents (Haase et al., 2014).

Contrary to prior findings (Bloemsma et al., 2022; Maes et al., 2021; Van Aart et al., 2018; Younan et al., 2016), we did not find associations of green space with either externalising or internalising problems. A possible reason is that Dutch adolescents' mental health may be affected by green space in a larger area beyond the neighbourhood with cycling as the primary travel mode (Bloemsma et al., 2018). Our reasoning is supported by another Dutch study reporting that green space-mental well-being associations among adolescents were robust for the 3 km residence-based buffer, but less consistent for smaller ones (Bloemsma et al., 2022).

5.3. Strengths and limitations

Strengths of this study include the use of nine-year longitudinal data and time-varying environmental measurements, allowing to simultaneously disentangle the effects of exposure levels and exposure changes on two broad mental health indicators throughout adolescence. Furthermore, we observed strong mutual-confounding effects among exposures on the estimates of some exposure-outcome associations. Our integration of multi-exposures largely mitigated the omission bias and improved the robustness of our findings.

We also acknowledge some limitations. First, causal inference is challenging to establish despite our longitudinal design. However, reverse causation may be unlikely for within-person associations which are robust to all time-invariants confounders related to selective migration. Since residence-selection is more parent-driven and adolescents are economically constrained, we also controlled for several parent-level confounders to mitigate such parent-related selection bias for between-person associations. Except for relocation, it is hard to imagine how adolescents can change their residential environments. Moreover, we minimised the risk of selection bias in between-person associations by removing movers from the sample in the sensitivity analyses. Second, we observed null within-person associations for green space, noise, and deprivation, possibly because temporal changes in these exposures are minor. Some uncertainties in the exposure data, such as variation in the cloudiness in the satellite images for the yearly NDVI estimate and the lack of locally modelled time-varying $PM_{2.5}$ data, remain. However, an additional assessment of the NDVI between 2001 and 2010 using different cloud-mask thresholds indicated nearly perfect correlations (Table S8). Still, we cannot entirely rule out that these data uncertainties in the exposure assessment might have affected the estimated associations. Third, we assumed that administrative areas properly represent the geographic context of the neighbourhood. This assumption may not always be correct since we cannot rule out that adolescents' perception of their neighbourhood was different from this administrative area (Fleckney & Bentley, 2021). Fourth, due to the lack of data on the exposure history before wave 1, we were unable to assess whether and how the duration of exposure might play a role in adolescents' mental health development. Finally, as with most other studies

(Bloemsma et al., 2022; Younan et al., 2016), we ignored that adolescents may also be affected by environmental exposures at activity locations outside the neighbourhood (e.g., school), possibly obscuring the actual mental health-effects of exposures (Brons et al., 2022).

6. Conclusion

Air pollution, noise, and deprivation may threaten adolescent mental health. Our findings indicated different associations of exposure levels and exposure changes with adolescent mental health problems and stressed the importance to include co-occurring environmental exposures. We found that adolescents with increased $PM_{2.5}$ exposure driven by residential moving showed increased externalising problems, whereas non-movers exposed to increased social fragmentation showed a minor decrease in internalising problems. Furthermore, adolescents exposed to higher noise levels showed more externalising problems, while higher deprivation and lower social fragmentation levels were associated with more internalising problems. Higher $PM_{2.5}$ concentrations were associated with more externalising problems when the concentrations exceeded 15 μg/m^3. Reductions in air pollution concentrations based on guidelines stricter than European Union's current air quality standards (25 μg/m^3 for $PM_{2.5}$) might be a target for future interventions aimed at mitigating the risk of mental health problems among adolescents. We advise future studies to consolidate our findings by decomposing within- and between-person longitudinal associations between multiple spatiotemporal environmental exposures and adolescent mental health.

CRediT authorship contribution statement

Yi Zeng: Conceptualization, Methodology, Formal analysis, Data curation, Visualization, Writing – original draft. **Gonneke W. J. M. Stevens:** Conceptualization, Methodology, Data curation, Supervision, Writing – review & editing. **Marco Helbich:** Conceptualization, Methodology, Supervision, Data curation, Writing – review & editing.

Declaration of Competing Interest

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

Data availability

The TRAILS survey data are available at https://www.trails.nl/en/hoofdmenu/data/data-use, subject to the approval of the TRAILS committee and data manager. The authors have no right to share the TRAILS data. Exposure data can be shared upon request.

innovation program (grant agreement No 714993).

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2023.108142.

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