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Changes in neighborhood physical and social environments matter for change in mental health: Longitudinal evidence from Dutch panel data☆

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ABSTRACT

Numerous neighborhood environments have been recognized to affect mental health, but only a few longitudinal studies investigated these associations jointly and whether different population groups are affected differently. We used three-wave panel data of 2699 adults between 2010 and 2016 in the Netherlands to assess the associations between changes in neighborhood physical and social environments and mental health changes. Further, we assessed possible effect modification of gender and income. Mental health was measured using the Mental Health Inventory. Time-varying exposure to green space, blue space, population density, air pollution, socioeconomic deprivation, and social fragmentation were assigned based on individuals' neighborhood histories. Fixed-effect regressions were conducted to assess within-person associations between single and multiple exposures on mental health for the entire sample and stratified by gender and income. Our single-exposure models showed that increases in blue space were significantly associated with mental health improvements, while increases in fine particulate matter ($PM_{2.5}$) resulted in declines in mental health. These associations were not attenuated in the multi-exposure model. We observed no significant associations for the remaining environments. Stratification analyses showed that females' mental health further declined as $PM_{2.5}$ concentrations increased compared to males. Increasing levels of socioeconomic deprivation were associated with further declines in mental health among the less well-off compared with higher-income earners. Our longitudinal findings suggested that neighborhood physical and social environment changes were associated with mental health changes. Future research is required to establish the underlying pathways.

1. Introduction

One in eight people face a mental illness worldwide (World Health Organization, 2022). For the Netherlands, the ratio is one in six (Statistics Netherlands, 2022a). Mental illness is among the leading contributors to the global disease burden (Patel et al., 2018), posing potentially significant threats to individuals' physical and social functioning (Campion et al., 2022).

The etiology of mental illness is complex (Patel et al., 2007). Studies have demonstrated that individual-level factors such as heredity, demographics, and socioeconomic factors explain only a portion of the risk of mental illness (Lund et al., 2018; Patel et al., 2018). Awareness is growing that the environmental characteristics of neighborhoods may contribute to individuals' susceptibility (Blair et al., 2014; Kim, 2008; Sui et al., 2022). Although some past study-specific findings have been inconsistent, systematic reviews and meta-analysis results tentatively suggest that higher concentrations of air pollution (Borroni et al., 2022), less green space (Yang et al., 2021), less blue space (Smith et al., 2021), pronounced socioeconomic deprivation (Sui et al., 2022), and greater social fragmentation (Ku et al., 2021) may put people at risk. The current understanding stems largely from cross-sectional studies which do not allow temporal assessments of environment-mental health relationships, which may, in turn, partly explain the inconsistent associations found in past studies (Baranyi et al., 2021; Barnett et al., 2018; de Keijzer et al., 2020; Rautio et al., 2018; Yen et al., 2009). Relevant longitudinal studies, while often more rigorous in design and allowing assessment of changing neighborhood environments and changing mental health (Diez Roux and Mair, 2010), remain scarce (Sui et al., 2022).

Existing longitudinal studies face three limitations: First, it is common to assess a single environment, even though it has been found that environments co-vary spatially (Chen et al., 2019; Rugel and Brauer,

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2020; Zhao et al., 2021). Therefore, not considering multiple environments (e.g., green space and air pollution) in a study risks inaccurate effect estimates (Wang et al., 2023). Second, studies typically measure environments only once at baseline (Liu et al., 2021; Tarkiainen et al., 2021). This practice is suboptimal because environments may vary over time. For example, neighborhood green space can shrink due to progressing urbanization (Yang et al., 2017), and individuals may experience spatiotemporally varying neighborhood environments due to residential relocation (Hagedoorn and Helbich, 2021). Therefore, measuring environments only once may lead to biased estimates of environment-health associations (Pearce et al., 2018; Wheeler et al., 2012). Tracking these neighborhood environmental changes becomes essential when studying long-term mental health outcomes. Third, existing longitudinal studies have usually assessed between-individual associations. These are prone to introduce residual confounding if unmeasured time-invariant factors (e.g., heredity, personality) are associated with the environmental exposure and the outcome (Allison, 2009; Gunasekara et al., 2013).

Previous studies have also suggested that health inequalities and environmental injustice exist; that is, environmental amenities and risks are unequally distributed across population groups (Brulle and Pellow, 2006; Ho et al., 2018; Silva et al., 2016). A review with meta-analyses noted that some environment-health associations are moderated by individuals' demographic and socioeconomic characteristics (Barnett et al., 2018). It was found that the adverse effects of living in disadvantaged neighborhoods were more pronounced among females (Bassett and Moore, 2013; Sullivan et al., 2022) and that the mental health benefits of exposure to green space (McEachan et al., 2016) and blue space appeared (Garrett et al., 2019) to be stronger for individuals with lower socioeconomic status (e.g., low income). However, these moderating effects of gender and income have rarely been examined longitudinally, and results have been inconsistent.

To address these gaps in research, we aimed first to investigate how the within-person changes in neighborhood physical and social environments are associated with within-person changes in mental health and second to examine whether gender and income moderate the associations. Two hypotheses were tested by applying fixed-effect regressions to three-wave panel data from Dutch adults. First, we speculated that adults' mental health improves when their neighborhood environments improve (i.e., more green or blue spaces, lower levels of population density, air pollution, socioeconomic deprivation, or social fragmentation). Second, we hypothesized that the associations between neighborhood environments and mental health are stronger among females and the less well-off.

2. Material and methods

2.1. Study sample

We conducted an observational study among adults aged ≥18 in the Netherlands. Our data were obtained from the Longitudinal Internet Studies for the Social Sciences (LISS) panel, an ongoing and representative survey of Dutch households maintained by Centerdata (Scherpenzeel and Das, 2010). Households were selected based on their residential address, originating from a probability sample drawn from the population register of Statistics Netherlands. Within the selected households, members were eligible to be included in the survey if they were at least 16 years of age and lived at their home address at least four days per week. A full description of the recruitment and the LISS sample is available elsewhere (Scherpenzeel, 2009).

The initial wave of the health survey was conducted in November 2007 and included 4200 households containing approximately 6700 individuals. We extracted data on respondents' mental health from three waves of the health module across the seven years, November 2010 ($N = 5718$, T_1), November 2013 ($N = 5379$, T_2), and November 2016 ($N = 5408$, T_3). These waves were chosen because longer follow-up time resulted in more pronounced changes in neighborhood environments. The wave-specific response rates were 77.6% (T_1), 86.5% (T_2), and 85.4% (T_3). Respondents received a 15 Euro per hour reward (van Boekel et al., 2017) for online questionnaire completion.

We performed a complete case analysis and removed all respondents with missing data (Fig. 1). Of the 5718 respondents at T_1, many were eliminated due to attrition during follow-up ($N = 2536$), other reasons including incomplete mental health records ($N = 7$), aged <18 ($N = 47$), incomplete individual characteristics ($N = 354$), and missing environmental characteristics ($N = 75$). In total, our sample included 2699 adults followed up with over three waves.

2.2. Measure of mental health

We used the self-administered Mental Health Inventory (MHI-5) to measure mental health (Ware et al., 2000). The MHI-5 is a valid and reliable instrument for assessing adults' mental health (Kelly et al., 2008; Ware and Gandek, 1998). The MHI-5 scale we applied comprised five questions that inquired into individuals' mental states during the preceding four weeks (see Supplementary Table S1). Each item had six response categories ranging from 'none of the time' to 'all of the time.' The answers were re-coded on a scale between 0 and 5, with the third and fifth questions reverse-coded to obtain the total MHI-5 scores, and then transformed to a 100-point scale following previous studies (Ringdal and Rootjes, 2022; van der Velden et al., 2019). An MHI-5 score of 0 indicated optimal mental health, whereas higher scores indicated mental health issues. Cronbach's alpha was 0.852, indicating high internal consistency.

2.3. Measures of time-varying neighborhood environments

We assumed respondents' exposure environments occurred within their neighborhoods. Due to privacy restrictions, respondents were

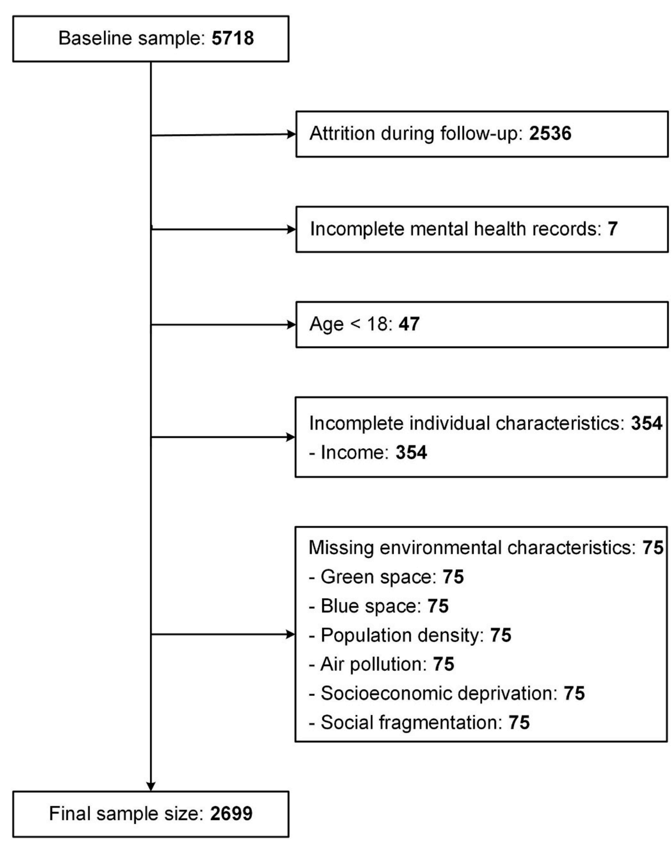

Fig. 1. Selection of the study population.

assigned to their four-digit postal code area instead of their home addresses. The neighborhood environmental characteristics were determined on the four-digit postal code level. The mean postal code area was 10.2 km^2 (standard deviation [SD] = 19.7) with a mean population of 4227 (SD = 4246) in 2018. Of note, Centerdata added minor random noise to each neighborhood environment to prevent the re-identification of respondents. The assigned random value was <1% of the median of each environment (see Supplementary Table S2). We obtained respondents' address locations on November 1st in the year each wave took place, allowing us to account for individuals who changed residence. Since 12.4% of our sample moved home at least once, tracing respondents along their moving trajectory increased the environment assessment accuracy (Hagedoorn and Helbich, 2021).

2.3.1. Green space

We used the normalized difference vegetation index (NDVI) (Tucker, 1979) from satellite imagery to map green space for each survey wave. Remote sensing data with a 30 m spatial resolution were obtained from Landsat images accessible through Google Earth Engine. Scenes with >40% cloud coverage and pixels with a cloudiness score of >25 were excluded. The images were obtained between May and September for each wave. The range of the NDVI is between −1 and +1, dependent on the earth surface's spectral reflectance. Higher positive values represent higher levels of vegetation. To avoid distortions of the NDVI values when calculating the mean per neighborhood, we masked pixels with values ≤ 0 (Gonzales-Inca et al., 2022; Hartley et al., 2021).

2.3.2. Blue space

We mapped blue space per wave through the normalized difference water index (NDWI) (McFeeters, 1996) based on satellite imagery similar to that used to calculate NDVI values. Pre-processing also underwent similar steps. The range of the NDWI was from −1 to 1, with values > 0 referring to water bodies (e.g., rivers, lakes, and seas). Pixels were transformed into binary maps distinguishing water-covered areas from dry land, allowing computing the proportion of pixels per neighborhood classified as bodies of water (Helbich et al., 2022).

2.3.3. Population density

Population density (i.e., 1000 inhabitants per km^2) was measured as the number of inhabitants within a neighborhood per wave. Population data were acquired from Statistics Netherlands.

2.3.4. Air pollution

We incorporated gridded average concentrations of ambient fine particulate matter ($PM_{2.5}$) (V4. EU.03) (Hammer et al., 2020; van Donkelaar et al., 2019). The GEOS-Chem chemical transport model was used to estimate surface concentrations by relating the aerosol optical depth from satellite retrievals to near-surface concentrations. Subsequently, ground-based observations were used to calibrate concentration estimates by geographically weighted regression. The moderate grid resolution of approximately 1 km ($0.01^\circ \times 0.01^\circ$) was resampled to 30 m because 8.4% of the postal code areas had a size of less than 1 km^2. We used bilinear interpolation to resample the gridded air pollution surface based on a weighted distance average of the four nearest input cells. Neighborhood-level mean annual averages of $PM_{2.5}$ concentrations per wave were determined.

2.3.5. Socioeconomic deprivation

Neighborhood-level socioeconomic deprivation was derived from Dutch population register data (Roberts et al., 2021). The composite score was based on summing the z-scores of three socioeconomic indicators (Allik et al., 2020): the unemployment rate, standardized median household income (reverse coded), and the fraction of households with a standardized income below the poverty line. Data on other dimensions considered (e.g., crime, housing quality) was not available. The index was computed based on all residents living in the same neighborhood using data on January 1st of every survey year. Higher index scores referred to higher levels of socioeconomic deprivation.

2.3.6. Social fragmentation

The social fragmentation index captured community integration (Fagg et al., 2008; Li et al., 2016). Input data were derived from Dutch population register data on January 1st of every survey year for all residents living in a given neighborhood. The index was composed of the sums of the z-scores of the proportion of adult residents (>18) who were unmarried, lived in a single-person household, and had moved to the address within 12 months (Hagedoorn and Helbich, 2021). Higher index scores referred to higher levels of social fragmentation.

2.4. Time-varying covariates

We extracted time-varying, individual-level covariates from the LISS background module (Elshout, 2019) based on previous studies (Cleary et al., 2019; Mark Noordzij et al., 2020). For each wave, we adjusted for age (in years), marital status (married, not married, never been married), household type (couple with children, couple without children, single with children, single, other), employment status (employed, unemployed), highest education level (low, medium, high), and household net income level grouped into tertiles (low, medium, high).

2.5. Statistical analyses

2.5.1. Descriptive and bivariate analyses

Means and standard deviations (SD) were used to summarize baseline individual and environmental characteristics of the whole and retained sample. We used Mann-Whitney U tests and Chi-squared tests to assess differences between the two samples. Further, we assessed mean changes in neighborhood environments across the waves. Spearman correlation coefficients (ρ) were used to examine the bivariate associations between multiple neighborhood environments. Generalized variance inflation factors (GVIF) were used to examine multicollinearity across the environments. Both the correlation coefficients and GVIF were calculated based on pooled data.

2.5.2. Fixed-effect regressions

We fitted fixed-effect regression models to assess within-person associations between the changes in MHI-5 scores and changes in environmental exposures (Allison, 2009). Fixed-effect models adjust for observed and unobservable time-invariant characteristics (e.g., heredity, personality) by using each individual as his/her control. Formally, the model is expressed as follows:

$$y_{it} = \beta x_{it} + \gamma Z_{it} + \alpha_i + \varepsilon_{it} \quad (1)$$

where y_{it} indicates the MHI-5 scores for individual i at time t; x_{it} represents the neighborhood environments of individual i living at time t; Z_{it} exhibits time-varying individual covariates; α_i accounts for individual fixed effects; and ε_{it} is the error term. We used the Hausman test to differentiate between the fixed-effect and random-effect model specifications. The analyses were conducted using the 'plm' package from R software, version 4.2.1 (Croissant and Millo, 2008).

In our primary analyses, we fitted single-exposure regressions to assess the association between each environmental exposure and the MHI-5 scores (Model 1a-1f). We assessed the combined effects of all environmental exposures by fitting a multi-exposure model (Model 2). Models 1 and 2 were covariate-adjusted for age, marital status, household type, employment status, education level, and income level.

In the secondary analyses, we assessed effect modification using gender and income. We first tested the effect modifications of gender by adding interaction terms (environmental exposure × gender) to the fully adjusted multi-exposure model (Model 3). Of note, in Models 1–3, we considered income groups as time-varying as had been done previously

(Astell-Burt et al., 2016; Noordzij et al., 2020; White et al., 2013). However, most respondents (70%) remained in the same income group across the three waves resulting in only minor variations. Therefore, we tested the environmental exposure × income interaction at baseline in Model 4.

2.5.3. Sensitivity analysis

We performed two sensitivity analyses. First, to assess whether moving status moderated the environmental exposure-mental health associations in the fully adjusted multi-exposure model, we added interaction terms. Second, mental illness sometimes can be heritable and can adversely affect family relationships. Thus, household members might share some risks (Merrill, 2022). Approximately 44% of the respondents had no other household members in the sample. To assess correlations of respondents sharing the same household, we randomly selected only one person per household ($N = 1945$) and refitted Model 2.

3. Results

3.1. Description of the sample

Table 1 summarizes the baseline characteristics of the whole and retained sample. The Mann-Whitney U and Chi-squared tests indicated that some individual-level characteristics differed significantly. Our study population ($N = 2699$) had good overall mental health with an average MHI-5 score of 24.99 (SD ± 16.94), 1324 (49.06%) were male, the mean baseline age was 52.84 years (SD ± 14.59), 65.32% were married, 44.68% were couples without children, 52.80% were employed, 38.64% were highly educated, and 33.33% were high income. Supplementary Table S3 shows the baseline sample characteristics stratified by gender and income. Supplementary Table S4 shows the mean changes (and SDs) in the neighborhood environments across the waves.

Table 1
Baseline characteristics of the retained and whole sample.

Variables [Mean (SD)]/[N (%)]	Retained sample ($N = 2699$)	Whole sample ($N = 5718$)	p-value
MHI-5 score	24.99 (16.94)	25.90 (16.88)[a]	0.021
Age (in years)	52.84 (14.59)	48.80 (17.35)	<0.001
Gender			0.020
Male	1324 (49.06%)	2648 (46.31%)	
Female	1375 (50.94%)	3070 (53.69%)	
Marital status			<0.001
Married	1763 (65.32%)	3276 (57.29%)	
Not married	405 (15.01%)	806 (14.10%)	
Never married	531 (19.67%)	1636 (28.61%)	
Household type			<0.001
Couple with children	848 (31.42%)	2119 (37.06%)	
Couple without children	1206 (44.68%)	2198 (38.44%)	
Single with children	101 (3.74%)	279 (4.88%)	
Single	518 (19.19%)	1063 (18.59%)	
Other	26 (0.96%)	59 (1.03%)	
Employment status			0.946
Employed	1425 (52.80%)	3025 (52.90%)	
Unemployed	1274 (47.20%)	2693 (47.10%)	
Education level			0.244
High	1043 (38.64%)	2172 (37.99%)	
Medium	819 (30.34%)	1837 (32.13%)	
Low	837 (31.01%)	1709 (29.89%)	
Income level			0.402
High	899 (33.33%)	1836 (34.8%)[b]	
Medium	900 (33.33%)	1710 (32.4%)[b]	
Low	900 (33.33%)	1728 (32.8%)[b]	
NDVI	0.45 (0.11)	0.45 (0.11)[c]	<0.001
Blue space	0.04 (0.12)	0.04 (0.12)[c]	<0.001
Population density (1000 inhabitants per km^2)	2.75 (3.20)	2.77 (3.25)[c]	<0.001
$PM_{2.5}$ (μg/m^3)	15.88 (1.99)	15.88 (1.97)[c]	0.973
Socioeconomic deprivation	0.24 (2.04)	0.24 (2.09)[c]	0.971
Social fragmentation	0.59 (2.31)	0.57 (2.33)[c]	0.783

Note:
[a] 16 participants were missing data for MHI-5 score at baseline.
[b] 444 participants had no data on the household net income at baseline.
[c] 168 participants had no neighborhood environmental data (e.g., due to a lack of postal code) at baseline.

3.2. Bivariate analyses

Fig. S1 shows the Spearman correlations between the MHI-5 scores and the environmental exposures. MHI-5 scores were negatively and weakly correlated with NDVI ($\rho = -0.05$, $p < 0.05$); the correlation with the proportion of blue space was non-significant ($\rho = -0.02$, $p = 0.07$). MHI-5 scores were weakly positively correlated with population density, $PM_{2.5}$ concentration, socioeconomic deprivation, and social fragmentation ($0.06 \leq \rho \leq 0.07$, $p < 0.05$).

NDVI was strongly and negatively correlated with population density ($\rho = -0.78$, $p < 0.05$), and socioeconomic deprivation was positively correlated with social fragmentation ($\rho = 0.62$, $p < 0.05$). Correlations between other environmental exposures (e.g., NDVI and blue space, $PM_{2.5}$, and population density) were significant but only moderately so ($-0.52 < \rho < 0.62$, $p < 0.05$).

3.3. Associations between mental health and neighborhood environments

All GVIF scores of the neighborhood environments were below the critical value of 10 (see Supplementary Table S5). With the highest GVIF score being 3.321, there was no indication of multicollinearity. The Hausman tests favored fixed-effect rather than random-effect model specification (see Supplementary Table S6).

Fig. 2 summarizes the estimated associations between the environmental exposures and the MHI-5 scores. Supplementary Tables S7–S10 depict the numeric model results. Our primary analyses showed minor differences in the within-person associations between the single-environment (Model 1) and the multi-environment models (Model 2). The results of M1a-1f showed that an increase in the proportion of blue space was associated with decreased MHI-5 scores ($\beta = -0.118$, 95% CI: [-0.218, -0.019]). In contrast, an increase in $PM_{2.5}$ was associated with increased MHI-5 scores ($\beta = 0.299$, 95% CI: [0.059, 0.538]). We observed null associations for the other exposures. Model 2 indicated that an increase in the proportion of blue space was associated with a decrease in MHI-5 scores ($\beta = -0.120$, 95% CI: [-0.226, -0.015]). In contrast, an increase in $PM_{2.5}$ concentrations was associated with increased MHI-5 scores ($\beta = 0.311$, 95% CI: [0.069, 0.553]). The other environments showed null associations with the MHI-5 scores.

In our secondary analyses, the multi-exposure model was stratified by gender. Compared with males, an increase in $PM_{2.5}$ was associated with an increase in females' MHI-5 scores ($\beta = 0.339$, 95% CI: [0.026, 0.652]). For the income-stratified model, we observed that an increase in socioeconomic deprivation was associated with a decrease in MHI-5 scores ($\beta = -2.016$, 95% CI: [-3.193, -0.840]) for medium-income earners compared with low-income earners.

The results of the sensitivity analyses are summarized in the Supplementary Tables S11–13. Supplementary Table S11 shows some variation of each environmental exposure between T_1 and T_3 for the entire sample and stratified by moving status. Refitting the model with interaction terms between the exposures and people's moving status (Model 5) did not indicate statistically significant effect moderations (0.08 < p-value <0.97) (see Supplementary Table S12). When using only one person per household, the model results (Model 6) yielded robust effect estimates compared to the full sample (see Supplementary Table S13).

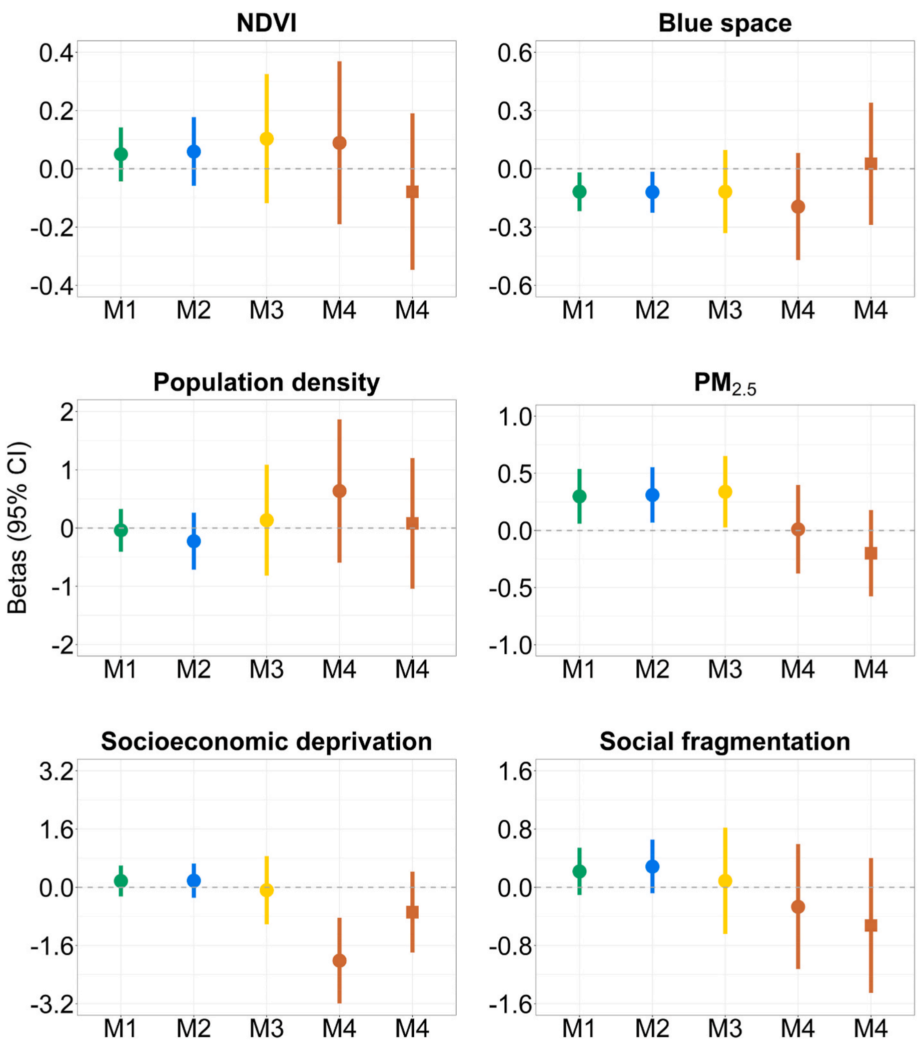

Fig. 2. Within-person associations between neighborhood-based environmental exposures and MHI-5 scores with 95% confidence intervals (CI). Effect estimates were based on fixed-effect regressions adjusted for age, marital status, household type, employment status, education level, and income level. Model 1 included each environmental exposure separately. Model 2 jointly included all environmental exposures. Model 3 included environmental exposure × gender interaction terms in the fully adjusted multi-exposure model. Model 4 included environmental exposure × income (at baseline) interaction terms in the fully adjusted multi-exposure model.

4. Discussion

4.1. Key findings

In this nationally representative Dutch panel study, we examined how changes in multiple neighborhood environments were associated with changes in adults' mental health. Complementing the mainly cross-sectional evidence base, our results indicated that increases in blue space were longitudinally associated with improvements in mental health. In contrast, increased air pollution concentrations were associated with declines in mental health. Because the remaining environmental exposures (i.e., green space, population density, socioeconomic deprivation, social fragmentation) showed null associations, our first hypothesis was only partially confirmed. Results of the stratified analyses, in line with our second hypothesis, showed that associations between neighborhood-based environmental exposures and mental health differed across gender and income. Females' mental health further declined with increased levels of air pollution compared with males. Furthermore, increasing socioeconomic deprivation was associated with further declines in mental health among the less well-off compared with higher-level income earners.

4.2. Explanation of findings and available evidence

We found that blue space benefited mental health, which is in line with attention restoration theory (Kaplan, 1995) and stress reduction theory (Ulrich et al., 1991). It did so by inducing positive emotions (Ulrich, 1983), esthetic pleasure, and relaxation (Herzog et al., 1997), all of which have been associated with improved mental health (Bowler et al., 2010). The association between air pollution and mental health was in line with longitudinal studies in the United States and the United Kingdom, which indicated that higher concentrations of $PM_{2.5}$ were associated with increased psychological distress (Sass et al., 2017) and mental illness (al Ahad et al., 2022). The following biological mechanisms could explain our finding. Inhaled fine air pollution particles entering the systemic circulation could reach the brain, then result in systemic oxidative stress and brain inflammation (Genc et al., 2012; Valavanidis et al., 2008), which is thought to play a role in developing mental illness (Anisman and Hayley, 2012; Barron et al., 2017).

Partially consistent with our finding, Sass et al. (2017) found that $PM_{2.5}$ concentrations were positively related to psychological distress among White women in the United States, while for White men, the $PM_{2.5}$-mental health association was null; no differences were found across other racial groups. Our finding that females' mental health declined more from increased exposure to air pollution may be because women spend more time near the home, for example, taking care of children or working part-time (Kavanagh et al., 2006). In 2013, net labor force participation was 61% of women versus 70% of men in the Netherlands (Statistics Netherlands, 2022b), and 70% of Dutch women worked part-time, compared to 26% of Dutch men (Statistics Netherlands, 2022c).

People living in socioeconomically deprived neighborhoods tend to experience higher risks for mental illness, possibly due to higher levels of crime or social disorganization (Sui et al., 2022). However, these risks were differentiated by income. Our study showed that increases in socioeconomic deprivation were associated with increased risk to lower-income earners. Such mental health-related inequalities have been noted in the previous literature (Fone et al., 2007; Weich et al., 2003). A possible explanation is that compared to higher-income earners, the less well-off lack access to individual health-supportive resources such as higher-quality healthcare, home security systems, and social support to protect them from the adverse effects of living in socioeconomically deprived neighborhoods (Riva et al., 2011; Stafford and Marmot, 2003).

The remaining environmental exposures (i.e., green space, population density, social fragmentation) were non-significantly associated with mental health. A possible explanation why we found null green space associations may be related to our green space measure. While the NDVI captures the overall amount of vegetation in a neighborhood well and is widely used (Banay et al., 2019; Pun et al., 2018; Triguero-Mas et al., 2015), the measure cannot distinguish between different vegetation types and private and public green spaces. However, the nonsignificant associations between green space and mental health was not specific to our study. In another longitudinal study in Eindhoven, the Netherlands, green space also showed a null association (Noordzij et al., 2020). However, these results conflicted with a British study (Alcock et al., 2014), which showed that moving to greener neighborhoods was associated with mental health improvements, and an Australian study (Cleary et al., 2019), which indicated the perception of green space in the suburb of residence was positively associated with psychological well-being. Comparison with previous studies in this context ought to be approached with care due to differences in national contexts and varying exposure assessments.

4.3. Strengths and limitations

Given that much of the available evidence is cross-sectional, a strength of our study was that we contributed new longitudinal evidence on the associations between multiple environmental exposure changes and mental health changes. Another strength was that the data included nearly 3000 people collected over seven years, resulting in statistically well-powered analyses. Furthermore, our fixed-effect regressions (Allison, 2009) reduced the risk of an omitted-variable bias due to unobservable and hard-to-measure confounders in between-person associations (Gunasekara et al., 2013). Instead of assuming that the studied environmental exposures were stable over time as done elsewhere (Astell-Burt and Feng, 2019; Joshi et al., 2017), our exposures and individual variables were time-varying across the waves. Such dynamic consideration results in more rigorous effect estimates of the environmental exposures. We also accounted for individuals' histories of residential moves (Hagedoorn and Helbich, 2021).

Nevertheless, some limitations to our study had to be acknowledged. First, approximately 44% of the baseline members dropped out during follow-up. A similar attrition bias was also reported in previous studies (Fewtrell et al., 2008; Zhao et al., 2009), which may explain the differences in the individual characteristics and environmental exposures between the whole versus retained samples. As such, due to a loss of representativeness, our results might not be fully generalizable across the Dutch population. Second, our participants' mental health outcomes were self-reported rather than based on diagnostic interviews, which might have introduced bias, including recall bias. Although we took care to include several confounders, there remained the likelihood that some potential time-varying confounders remained unadjusted (Alcock et al., 2014; Astell-Burt et al., 2015). Third, we could only assess environmental exposures at the place of residence as typical practice in previous studies (Hautekiet et al., 2022; Pun et al., 2018; Yu et al., 2022). This limitation disregarded the fact that people were also exposed to other activity places (e.g., work).

Furthermore, we assumed that people's home environments were well-represented by small-scale postal code areas. We acknowledge that this analytical decision was suboptimal and that use of exact home addresses would be more accurate (Flowerdew et al., 2008; Gonzales-Inca et al., 2022). Although impossible in our case due to privacy restrictions, individualized geographic context delineations might have a lower measurement error. However, a comparative study in Amsterdam, the Netherlands, reported that green space measures were strongly correlated across different context definitions (i.e., circular and network buffers vs. administrative units), and green space-mental health associations were consistent (Helbich et al., 2021). Likewise, some minor random noise was added to the neighborhood-based environmental exposure data to circumvent the re-identification of respondents. We could not exclude the possibility that this precaution might affect our effect estimates slightly. Finally, our study was observational, and causalities could not be inferred.

5. Conclusions

Our study contributed to the slowly growing evidence on the longitudinal associations between changes in neighborhood determinants and changes in adults' mental health. Our novel findings suggested that mental health improvements were associated with increased blue space, while increased air pollution levels had harmful effects. Null within-person associations were observed for green space, population density, socioeconomic deprivation, and social fragmentation. Furthermore, we found that the associations were moderated by gender and income. Compared with males, females' mental health declined further with increased air pollution levels. The mental health of people less well-off declined with increases in socioeconomic deprivation, compared with higher-income earners. Future longitudinal studies are warranted to assess the possible long-term effects of neighborhood environments on individuals after they relocate and to improve understanding of the underlying causal pathways in associations between neighborhood environments and mental health.

Credit author statement

Yuwen Sui: Conceptualization, Data curation, Methodology, Formal analysis, Visualization, Writing – original draft, Funding acquisition. Dick Ettema: Supervision, Writing – review & editing. Marco Helbich: Supervision, Data curation, Conceptualization, Writing – review & editing.

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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.

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Appendix A. Supplementary data

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