Health & Place 77 (2022) 102893

Contents lists available at ScienceDirect

Health and Place

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

Longitudinal associations between the neighborhood social, natural, and built environment and mental health: A systematic review with meta-analyses

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ARTICLE INFO

Keywords:
Residential neighborhood
Exposure
Mental disorders
Cohort studies
Panel studies

ABSTRACT

This review aimed to assess the longitudinal associations between neighborhood social, natural, and built environments, and multiple mental health outcomes (i.e., depression, anxiety, common mental disorder, and pooled mental disorders). Of 6,785 records retrieved, 30 studies fulfilled the inclusion criteria. Meta-analytical results primarily obtained from developed country studies showed that composite neighborhood socioeconomic status was negatively associated with depression ($p = 0.007$) and pooled mental disorders ($p = 0.002$), while neighborhood urbanicity was positively associated with depression ($p = 0.012$) and pooled mental disorders ($p = 0.005$). Future longitudinal studies with similar designs and standardized exposure assessments are warranted.

1. Introduction

Mental disorders are a significant public health concern (Patel et al., 2018). Approximately 10% of the world's population faced mental disorders in 2013, increasing to 13% in 2020 (World Health Organization, 2016, 2020). The causes of mental disorders are complex, including biological, socioeconomic, and psychological factors (Lund et al., 2018; Patel et al., 2018). Evidence is also mounting that people's living environments, including the social (e.g., area-level socioeconomic status (SES)), natural (e.g., green spaces), and built (e.g., urbanicity) dimensions, are related to mental health (Meijer et al., 2012; van den Berg et al., 2015; Van Holle et al., 2012). However, the available evidence is mainly cross-sectional, failing to assess exposures over time (Helbich, 2018; Pearce et al., 2018), and cannot address causality (Besser et al., 2021) or selection effects (Barnett et al., 2018).

Longitudinal designs (e.g., cohort and panel studies), by contrast, provide opportunities to examine causal environmental effects on mental health and how environmental changes relate to mental health trajectories (Hedeker and Gibbons, 2006). However, extant longitudinal research only provides a limited and inconsistent evidence base. Moreover, the research has also provided conflicting results possibly caused at least partially due to heterogeneous outcome definitions, variations in statistical modeling, heterogeneity in environmental exposure assessments, and analysis of different population groups (Caruana et al., 2015; Noordzij et al., 2020). Thus, to overcome the discrepancies in results across individual studies, quantitative syntheses of the results of multiple studies are essential to better understand the longitudinal associations between the neighborhood environment and mental health.

Six systematic reviews on longitudinal associations between the neighborhood environment and mental health have been performed. However, these reviews exhibited three types of limitations. First, three reviews only assessed a single neighborhood characteristic, namely neighborhood SES (Richardson et al., 2015), green spaces (de Keijzer et al., 2020), and crime (Baranyi et al., 2021), while other neighborhood environmental characteristics (e.g., social cohesion, blue spaces, access to services) remained unrecognized. Second, two reviews (Barnett et al., 2018; Yen et al., 2009) assessed neighborhood social and physical environments, but the study populations were only restricted to older adults. Third, the review by Rautio et al. (2018) provided a narrative synthesis on the associations between living environment and mental health but did not provide any meta-analytical evidence. Given the availability of a growing number of longitudinal studies on the associations between neighborhood environments and mental health, a comprehensive statistical assessment of how the social, natural, and built neighborhood environments relate to the mental health of adults is indicated.

To address the research gap, we systematically reviewed the evidence of the longitudinal associations between neighborhood social,

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https://doi.org/10.1016/j.healthplace.2022.102893
Received 28 April 2022; Received in revised form 24 July 2022; Accepted 4 August 2022
Available online 18 August 2022
1353-8292/

natural, and built environments versus depression, anxiety, and common mental disorder (i.e., symptoms of depression and/or anxiety) (World Health Organization, 2016). We then appraised the risk of bias of the available evidence and conducted meta-analyses for each neighborhood environmental characteristic.

2. Methods

We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Supplementary Table S1) (Page et al., 2021). The review protocol was registered beforehand on PROSPERO in May 2021 (Registration number: CRD42021251896).

2.1. Eligibility criteria

Only peer-reviewed journal papers were included from inception to June 1, 2021. We excluded unpublished papers, conference papers, book chapters, dissertations, and review papers. There was no restriction on geography, and only English language studies were selected.

The inclusion criteria were, a priori, defined following the population-exposure-outcome framework (Page et al., 2021). The populations of the selected studies were composed of adults aged ≥18 years. The participants in these studies were initially assessed for their depression, anxiety, and common mental disorder levels. Each study, at minimum, also performed at least one follow-up assessment. We included papers that quantitatively (including environmental perceptions measured by Likert scales) assessed aspects of the social, natural, and built outdoor environments of studied residential neighborhoods.

2.2. Search strategy

Five databases were searched: Web of Science, Scopus, Embase, PubMed, and PsycInfo. The search query included items on the study design (e.g., 'longitudinal', 'cohort', 'follow-up'), geographic scope (e.g., 'neighborhood', 'community', 'residential'), environment exposure (e.g., 'natural environment', 'built environment', 'social environment'), and mental health (e.g., 'mental health', 'mental disorder', 'depression', 'anxiety'). For the complete search strategy for each database, see Supplementary Table S2.

2.3. Study selection

Eligible records were downloaded and imported into the Mendeley Reference Management software package. After removing duplicated records, the first author screened the titles and abstracts of the queried studies for eligibility. The authors discussed record eligibility until a consensus was reached on each one. All eligible records were then full-text screened by the first author. Reasons for full-text exclusion are reported in Supplementary Table S3.

2.4. Data extraction and narrative summary

We extracted the lead author, year of publication, location (i.e., country), and study population (i.e., sample size and age at baseline) from each eligible study. Additionally, we extracted measures for mental health (i.e., depression, anxiety, and common mental disorder), neighborhood-based social environments (i.e., SES, disorder and nuisance, residential stability, demographic heterogeneity, social cohesion, violence, safety, and trust), natural environments (i.e., available (types of) green spaces, quality of green spaces, and blue spaces) and built environments (i.e., aesthetic qualities, proximity to roadways, urbanicity, walkability, access to services, land use mix, and population density). Finally, we extracted the characteristics of each study's longitudinal measures (i.e., number of waves, follow-up duration, longitudinal design). Data were processed using a self-developed standardized data extraction form.

2.5. Risk of bias within individual studies

The Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies (National Heart and Blood Institute, 2014) was used to appraise the risk of bias in the studies, following previous practice (An et al., 2017; Baranyi et al., 2021). This assessment tool was initially designed for studies incorporating a single exposure, single outcome, and participants from a single country, so every item could be scored either as 'fulfilled' (1 point) or as 'not fulfilled', 'not applicable', or 'could not be determined' (0 points). However, in our review, some studies incorporated more than one factor (i.e., multiple exposures, multiple outcomes, participants from numerous countries), creating difficulties in some instances with classification by binary criteria. Therefore, we redesigned the scoring criteria for each item as 'fulfilled' (1 point), 'not fulfilled, 'not applicable', 'cannot be determined' (0 points), or 'partially fulfilled' (0.5 points) (Supplementary Table S4).

Fourteen items were employed to assess the study questions, design, exposure measurements, and outcomes. Each study was given an overall quality score from 0 to 14 points by summing the individual item scores. Studies with a total score of 0–4 were judged as high risk of bias, those that scored 5–9 as moderate risk of bias, and those that scored 10–14 as low risk of bias. The first author assessed each study's quality, and any disagreement was discussed between the authors until consensus was reached.

2.6. Meta-analysis

Higgins et al. (2019) divided study heterogeneity into each of clinical (i.e., variability in the participants, interventions, and outcomes), methodological (i.e., variability in study design and risk of bias), and statistical heterogeneity (i.e., variability in the intervention effects). The random-effects model addresses statistical heterogeneity. However, the heterogeneity of the included studies was of a clinical and methodological nature referring to diversity in environmental exposures and their assessments as well as diversity in longitudinal study designs, which cannot be adequately addressed by means of the random-effects model. To overcome these heterogeneity issues and the resulting incomparability of effect sizes, we used the weighted-z method (Whitlock, 2005) to calculate the pooled p-values rather than pooled effect sizes.

Associations between the same neighborhood environment and mental health outcome were pooled, and the directions of the association together with the p-value were extracted. At least five associations (several studies provided multiple associations) were considered sufficient for our meta-analytical synthesis (Higgins et al., 2009). Associations with $p < 0.05$ were judged as statistically significant, associations with $p \geq 0.05$ were judged as null. Assuming a normal distribution, the p-value was matched with the corresponding z-value (e.g., a significantly positive/negative association with $p < 0.05$ refers to a z-score of ± 1.96). The following equation was applied to obtain a weighted z-value across the j association:

$$z = \frac{\sum w_j \times z_j}{\sqrt{\sum w_j^2}} \quad \text{(Equation 1)}$$

To reduce the risk of bias in the z-scores, larger samples and higher quality scores received higher weights w. The sample size is related to the statistical power, and the quality score aims to capture the overall quality of the study. Similar weighting schemes were applied in previous reviews based on the weighted-z method (Barnett et al., 2018; Cerin et al., 2017; Chandrabose et al., 2019). Samples with ≤100 participants were weighted with 0.25, those with 101–300 with 0.50, those with 301–500, 501-1,000, and 1,001–2,500 were weighted with 1.00, 1.25, and 1.50, respectively. For >2,500 participants, the weight was 1.75. Similar weightings were used elsewhere (Chandrabose et al., 2019). In case a study used a different operationalization to delineate the geographic context (e.g., different buffer sizes), a fractional score was used (Cerin et al., 2017) (Supplementary Table S5). Multiple sensitivity analyses examined the robustness of the meta-analysis. Our first sensitivity analysis used weights solely based on the sample size; the second only used the quality score to obtain the weights; and in the third, we used an equal weight of 1 for each association.

3. Results

3.1. Study retrieval

We identified 6,785 studies, as detailed in Fig. 1. After eliminating duplicates, 4,006 papers were screened by title and abstract, of which 143 studies were eligible for full-text screening. We excluded 113 of these studies, as summarized in Supplementary Table S3. The final 30 studies met our inclusion criteria.

3.2. Study locations

Table 1 summarizes the study characteristics. The reviewed studies were drawn from 11 different countries. However, nearly half were U.S. studies ($n = 14$). Most of the remaining studies came from Sweden ($n = 5$), the United Kingdom ($n = 3$), the Netherlands ($n = 2$), and Japan ($n = 2$). Studies from low- and middle-income countries were underrepresented ($n = 3$). Two were European multi-country studies (Baranyi et al., 2019; Tarkiainen et al., 2021). Seventy percent ($n = 21$) were published after 2015.

3.3. Study population

Sample sizes ranged from 109 (Dzhambov, 2018) to 6,998,075 individuals (Crump et al., 2011). About 60% of the studies ($n = 18$) included more than 2,500 people; only two considered <300 people (Dzhambov, 2018; O'Donnell et al., 2015). Approximately half of the studies recruited people aged ≥50 years. Six studies focused on specific

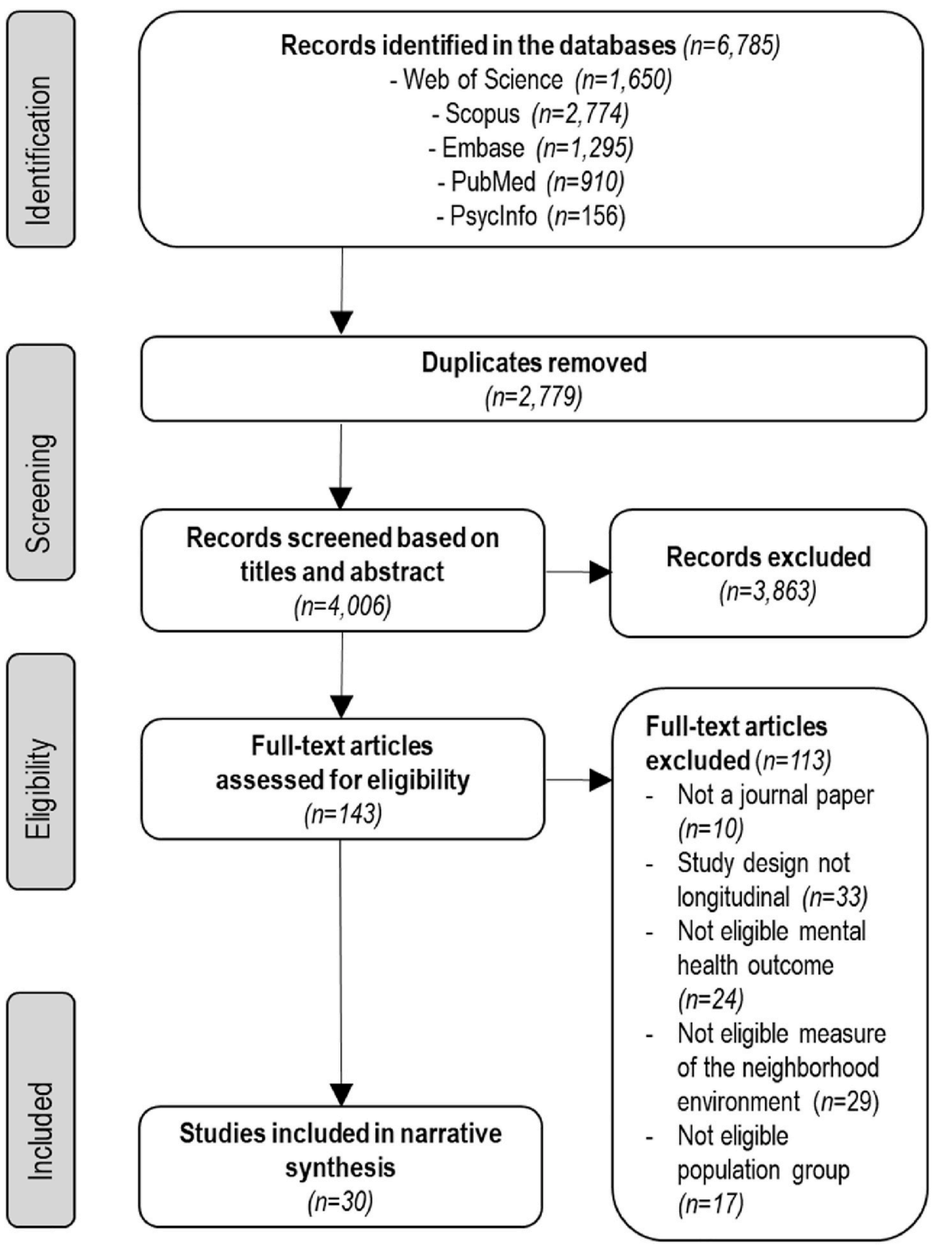

Fig. 1. Study selection based on PRISMA.

Table 1
Characteristics of the eligible studies.

Author and publication year	Location	Sample size	Age (at baseline)	Mental health outcome and measurement tool	Cut-off values used to distinguish between mental health and illness	Neighborhood area delineation, environmental exposure, measurement type	Number of waves	Follow-up duration	Longitudinal design	Results
Galea et al. (2007)	USA	$n = 820$	18+	Depression; modified versions of SCID and SMMD	Symptoms of ≥5	Community districts; poverty; objective	3	0.5 years and 1.5 years	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	Neighborhood poverty was positively associated with depression incidence
Schootman et al. (2007)	USA	$n = 672$	Middle-aged	Depression; 11-item CES-D	Score of ≥9	Block groups and census tracts; deprivation; objective	2	3	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	Null association between neighborhood deprivation and depression incidence
Bierman (2009)	USA	$n = 836$	65+	Depression; 4-item HSC	/	Participant delimitation; disorder; subjective	2	2	DV = $MH_{follow-up} - MH_{baseline}$ IV = $E_{baseline}$	Neighborhood disorder was positively associated with worsening levels of depression
Beard et al. (2009)	USA	$n = 808$	50+	Depression; 9-item PHQ	/	Census tracts; SES, residential stability, racial/ethnic composition; objective	2	2	DV = $MH_{follow-up} - MH_{baseline}$ IV = $E_{baseline}$	Neighborhood SES was negatively associated with worsening levels of depression; residential stability and racial/ethnic composition showed null associations
Mair et al. (2009)	USA	$n = 1{,}919$	45–84	Depression; 20-item CES-D	Score of ≥16	Participant delimitation; social cohesion, violence, and aesthetic qualities; subjective	3	3–4 years and 4–5 years	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	Null associations between neighborhood social cohesion, violence, aesthetic qualities and depression
Stafford et al. (2011)	UK	$n = 8{,}781$	50+	Depression; 8-item CES-D	/	Participant delimitation; social cohesion, safety; subjective	2	2	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	Neighborhood social cohesion was negatively associated with depression; neighborhood safety showed a null association
Crump et al. (2011)	Sweden	$n = 6{,}998{,}075$	18+	Depression, anxiety; antidepressant and anxiolytic prescriptions	/	Small area market statistics; deprivation; objective	2	2.5	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	Neighborhood deprivation was positively associated with antidepressant and anxiolytic prescription rates
Fone et al. (2014)	UK	$n = 4{,}426$	18–74	Common mental disorder; 5-item MHI	/	Census enumeration districts; deprivation; objective	2	7	DV = $MH_{follow-up} - MH_{baseline}$ IV = $E_{baseline}$	Neighborhood deprivation was positively associated with worsening levels of common mental disorder
Choi et al. (2015)	USA	$n = 5{,}326$	65+	Depression; 2-item PHQ	Score of >3	Participant delimitation; social cohesion; subjective	2	1	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	Null association between neighborhood social cohesion and depression
Murayama et al. (2015)	Japan	$n = 655$	65–84	Depression; GDS	Score of ≥6	Postal districts; social cohesion; subjective	2	2	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	Null association between neighborhood social cohesion and depression
O'Donnell et al. (2015)	USA	$n = 179$	30+	Depression; 9-item PHQ	Score of ≥5	Census tracts; social affluence, advantage, residential stability; objective	2	0.25	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	Neighborhood social affluence, residential stability, and neighborhood advantage were negatively associated with depression
Mair et al. (2015)	USA	$n = 548$	45–84	Depression; 20-item CES-D	/	Census tracts; social cohesion, violence, aesthetic qualities, safety, stress; subjective	2	5	DV = $MH_{follow-up} - MH_{baseline}$	Null associations between changes in neighborhood social cohesion, violence, aesthetic qualities,

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Table 1 (*continued*)

Author and publication year	Location	Sample size	Age (at baseline)	Mental health outcome and measurement tool	Cut-off values used to distinguish between mental health and illness	Neighborhood area delineation, environmental exposure, measurement type	Number of waves	Follow-up duration	Longitudinal design	Results
									IV = $E_{follow-up} - E_{baseline}$	safety, stress and changes in depression
Moore et al. (2016)	USA	$n = 5{,}475$	45–84	Depression; 20-item CES-D	/	Participant delimitation; safety, social cohesion; subjective	2	12	DV = $MH_{follow-up} - MH_{baseline}$ IV = $E_{follow-up} - E_{baseline}$	Null association between changes in neighborhood safety and social cohesion and changes in depression
Joshi et al. (2017)	USA	$n = 3{,}497$	65–75	Depression; 9-item PHQ	/	1-km network buffer; poverty; objective	3	2	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	Neighborhood poverty was positively associated with depression
Ruiz et al. (2018)	UK	$n = 11{,}037$	50+	Depression; 8-item CES-D	/	Participant delimitation; social cohesion; subjective	7	12	DV = $MH_{follow-up}$ IV = $E_{baseline}$	Null association between neighborhood social cohesion and depression
Yamaguchi et al. (2019)	Japan	$n = 29{,}065$	65+	Depression; 15-item GDS	Score of ≥5	School districts; social cohesion; subjective	2	3	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	Null association between neighborhood social cohesion and depression incidence
Motoc et al. (2019)	The Netherlands	$n = 3{,}772$	55+	Depression; 20-item CES-D Anxiety; 7-item HADS-A	/	Postal code area; social-economical position, average income, percent low-income earners, average house price, percent immigrants 1-km radius buffer; urban density; objective	5	14	DV = $MH_{follow-up}$ IV = $E_{multiple\ time\ points}$	Neighborhood percentage of immigrants, urban density were positively associated with depression and anxiety; null associations between neighborhood social-economical position, average income, percent low-income earners, average house price, depression and anxiety
Annerstedt et al. (2012)	Sweden	$n = 9{,}230$	18–80	Common mental disorder; 12-item GHQ	Score of ≥3	300-m radius buffer; available (types of) green spaces; objective	2	6	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	Null associations between neighborhood available (types of) green spaces and common mental disorder
van den Bosch et al. (2015)	Sweden	$n = 1{,}419$	18–80	Common mental disorder; 12-item GHQ	/	300-m radius buffer; available types of green spaces; objective	2	6	DV = $MH_{follow-up} - MH_{baseline}$ IV = $E_{follow-up} - E_{baseline}$	Null association between changes in neighborhood available types of green spaces and changes in common mental disorder
Weimann et al. (2015)	Sweden	$n = 9{,}444$	18–80	Common mental disorder; 12-item GHQ	Score of ≥3	1-km radius buffer; quality of green spaces; subjective	3	10	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	Null association between quality of green spaces and common mental disorder
Pun et al. (2018)	USA	$n = 4{,}118$	57–85	Depression; 11-item CES-D Anxiety; 7-item HADS-A	/	1-km radius buffer; available green spaces; objective	2	6	DV = $MH_{follow-up}$ IV = $E_{multiple\ time\ points}$	Null association between neighborhood available green spaces and depression and anxiety
Dzhambov (2018)	Bulgaria	$n = 109$	18–35	Common mental disorder; 12-item GHQ	/	100-m, 300-m, and 500-m radius buffer; available green spaces; objective 300-m and 500-m radius buffer; blue spaces; objective	2	0.6	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	Neighborhood available green spaces was negatively associated with incidence of common mental disorder; neighborhood blue spaces were negatively associated with incidence of common mental disorder within a 300-m radius

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Table 1 (*continued*)

Author and publication year	Location	Sample size	Age (at baseline)	Mental health outcome and measurement tool	Cut-off values used to distinguish between mental health and illness	Neighborhood area delineation, environmental exposure, measurement type	Number of waves	Follow-up duration	Longitudinal design	Results
										buffer, but null association using a 500-m buffer
Astell-Burt and Feng (2019)	Australia	$n = 39{,}277$	45+	Common mental disorder; physician diagnosis	/	1-mile road network buffer; available (types of) green spaces; objective	2	6	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	Null associations between available (types of) green spaces and common mental disorder
Banay et al. (2019)	USA	$n = 38{,}947$	54–91	Depression; physician diagnosis or antidepressant prescription	/	250-m and 1.25-km radius buffer; available green spaces; objective	2	10	DV = $MH_{follow-up}$ IV = $E_{multiple\ time\ points}$	Available green spaces were negatively associated with depression incidence within 250-m buffer but null association using 1.25-km buffer
Noordzij et al. (2020)	The Netherlands	$n = 3{,}175$	Mean age = 53	Common mental disorder; 5-item MHI	/	300-m, 500-m and 1-km radius buffer; available green spaces; objective	3	10	DV = $MH_{follow-up} - MH_{baseline}$ IV = $E_{follow-up} - E_{baseline}$	Null association between change in available green spaces and change in common mental disorder
Pun et al. (2019)	USA	$n = 4{,}118$	Mean age = 70	Depression; 11-item CES-D Anxiety; 7-item HADS-A	/	1-km road network buffer; proximity to the roadway, urbanicity; objective	2	6	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	Proximity to roadways was positively associated with depression and anxiety; urbanicity was positively associated with depression but showed a null association with anxiety
Alfredo Fernandez-Nino et al. (2019)	Mexico	$n = 996$	55+	Depression; mean of medical diagnosis and CIDI	Score of ≥2 in set A and score of ≥4 in set B of questionnaire/ history of medical diagnosis of depression	50-m by 950-m length road network buffers; total length of street spaces related to walkability Participant; objective delimitation; social capital, trust and solidarity, safety; subjective	2	4	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	Null associations between length of neighborhood street spaces related to walkability, social capital, trust and solidarity, safety, and depression incidence
Baranyi et al. (2019)	18 countries in Europe	$n = 10{,}328$	50–96	Depression; 12-item EURO-D	Score of ≥4	Participant delimitation; access to services, nuisances; subjective	6	at least 6	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	Access to services was negatively associated with depression incidence; neighborhood nuisance was positively associated with depression incidence
Liu et al. (2021)	China	$n = 2{,}081$	65–101	Depression; 15-item GDS	/	200-m and 500-m road network buffer; available green spaces, land use mix, service facilities; objective	4	3	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	The number of community centers within a 500-m buffer was negatively associated with depression but a null association using a 200-m buffer; null associations between available green spaces, land use mix, public transportation terminals, and commercial, cultural, active leisure, passive leisure facilities and depression
Tarkiainen et al. (2021)	Italy, Sweden, Finland	$n = 347{,}647$ (Italy) $n = 431{,}361$ (Sweden) $n = 94{,}347$ (Finland)	50+	Depression; antidepressant prescription	/	Postal-code area; the proportion of residents with basic education, living in rented dwellings, the unemployment rate, available green areas, urbanicity,	At least 2	6	DV = $MH_{follow-up}$ IV = $E_{one\ time\ point}$	Proportion of basic educated and unemployed people were negatively associated with antidepressant prescription rates in Turin; proportion of basic educated people was negatively associated

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Table 1 (*continued*)

Author and publication year	Location	Sample size	Age (at baseline)	Mental health outcome and measurement tool	Cut-off values used to distinguish between mental health and illness	Neighborhood area delineation, environmental exposure, measurement type	Number of waves	Follow-up duration	Longitudinal design	Results
						population density, land use mix; objective				with antidepressant prescription rates in Stockholm; urbanicity, land use mix, and population density were positively associated with antidepressant prescription rates in Stockholm; land use mix and population density were positively associated with antidepressant prescription rates in Finnish cities

Abbreviations. SCID: Structured Clinical Interview for Diagnostic; SMMD: Statistical Manual of Mental Disorders; CES-D: Center for Epidemiologic Studies Depression scale; HSC: Hopkins Symptoms Checklist; PHQ: Patient Health Questionnaire; MHI: Mental Health Inventory; GHQ: General Health Questionnaire; GDS: Geriatric Depression Scale; HADS-A: Hospital Anxiety and Depression Scale; CIDI: Composite International Diagnostic Interview; EURO-D: A European Union initiative to compare symptoms of depression in 14 European centers; DV: dependent variables; IV: independent variables; MH: mental health; E: environment.

population groups such as African Americans (Schootman et al., 2007), university students (Dzhambov, 2018), women (Banay et al., 2019), or respondents with Type 2 diabetes and depression (O'Donnell et al., 2015).

3.4. Longitudinal assessment of the outcome

Mental health outcomes were typically assessed over two waves (70%, $n = 21$), while only three studies used more than five waves (Baranyi et al., 2019; Motoc et al., 2019; Ruiz et al., 2018). The follow-up period ranged from three months (O'Donnell et al., 2015) to 14 years (Motoc et al., 2019), with an average duration of 5 years. We identified four types of longitudinal designs (Supplementary Table S6). In 77% of the studies, mental health at the follow-up was analyzed; by contrast, 23% assessed a change score of mental health outcome between baseline and follow-up as the dependent variable.

3.5. Mental health outcomes

Twenty-three out of the 30 studies assessed depression as the outcome (77%). Most studies ($n = 19$) adopted self-reported questionnaires; only three used (self-reported) physician diagnoses or antidepressant prescriptions (Banay et al., 2019; Crump et al., 2011; Tarkiainen et al., 2021). The Center for Epidemiologic Studies Depression scale (CES-D) was used nine times, with six other questionnaires also applied in other studies (e.g., the Patient Health Questionnaire (PHQ) and the Geriatric Depression Scale (GDS)). Seven studies assessed common mental disorder; six used the self-reported General Health Questionnaire (GHQ) and the Mental Health Inventory (MHI); only one was based on self-reported physician diagnoses (Astell-Burt and Feng, 2019). Anxiety was examined in four studies, with three employing the Hospital Anxiety and Depression Scale (HADS-A), and one using anxiolytics prescriptions (Crump et al., 2011).

3.6. Neighborhood environment

Exposures were typically only measured once ($n = 23$, 77%). Twenty-one of the studies estimated the exposure at baseline. Only 10% ($n = 3$) of the studies investigated the change of environmental exposures between baseline and follow-up; 13% ($n = 4$) assessed exposures $\geq$3 times (Banay et al., 2019; Motoc et al., 2019; Noordzij et al., 2020; Pun et al., 2018).

Nine dimensions of the social environment were examined in 20 studies. The majority investigated neighborhood social cohesion ($n = 9$) and neighborhood SES ($n = 9$), and we divided neighborhood SES into composite neighborhood SES, which is measured by a composite index (e.g., comprehensively considering income, education, and occupation) ($n = 5$), and single neighborhood SES assessed by only a single variable (e.g., only measuring income or education or wealth) ($n = 5$). Neighborhood safety ($n = 4$), disorder, and nuisance were captured four times, primarily through community surveys. Only three studies dealt with neighborhood violence (Mair et al., 2009, 2015) or trust (Alfredo Fernandez-Nino et al., 2019). The remainder focused on residential stability (Beard et al., 2009; Motoc et al., 2019) and demographic heterogeneity (Beard et al., 2009).

Eleven studies focused on neighborhood natural environments. Most assessed the available green spaces ($n = 8$), commonly measured through the remote sensing-based normalized difference vegetation index (NDVI) or land use data. Four studies distinguished green space types (e.g., lush, grass) (Alfredo Fernandez-Nino et al., 2019; Annerstedt et al., 2012; Astell-Burt and Feng, 2019; van den Bosch et al., 2015). The quality of green spaces (Weimann et al., 2015) and blue spaces (Dzhambov, 2018) was rarely examined. Built environment-mental health associations were examined in seven studies. The studies primarily drew from land use data or road-network data and addressed aesthetic qualities (Mair et al., 2015), proximity to roadways (Pun et al., 2019), urbanicity (Motoc et al., 2019; Pun et al., 2019; Tarkiainen et al., 2021), walkability (Alfredo Fernandez-Nino et al., 2019), access to services (Baranyi et al., 2019; Liu et al., 2021), land use mix (Liu et al., 2021; Tarkiainen et al., 2021), and population density (Tarkiainen et al., 2021).

3.7. Exposure assessment

Different approaches were used to assess the neighborhood environment. Thirteen studies used geographic information system (GIS) based buffers, most centered on residential addresses. Eleven studies used administrative units, while eight allowed the participants to delimit the extent of their living environments.

3.8. Quality assessment and risk of bias

Our quality assessment revealed that 30% of the studies exhibited a low risk of bias and 70% exhibited a moderate risk of bias; none was rated as having a high risk of bias (Supplementary Table S7). The assessment tool investigated how reasonable the research question, selection of study participants, measurement of exposure and outcome, and the set of confounders was. For some questions, the majority of studies obtained one point (e.g., "Was the research question or objective in this paper clearly stated?"). This contributed to the fact that all included studies obtained a quality score of at least 4 points and none of the studies was evaluated as of high risk of bias. Nevertheless, the quality scores ranged from 6 to 12 across the studies.

We identified three possible reasons for a risk of bias (Fig. 2). First, if fewer than 50% of eligible people participated at baseline, and more than 20% of the baseline participants were lost at follow-up, then the study population possibly does not represent the target population adequately. In 40% of the included studies, fewer than 50% of eligible people participated in each study. In 73% of the included studies, the loss on follow-up was more than 20%. Second, to determine whether an exposure causes an outcome, the exposure must occur before the outcome. Note, multiple exposure assessments permit examining changes in exposures over time. Compared with environmental perceptions, objective measurements were supposed to be more accurate and reliable. Sixty percent of the reviewed studies assessed the exposures at the time when the outcomes were measured (or thereafter); 73% measured the environmental exposures only once; 33% dealt with individuals' environmental perceptions. Third, most studies ($n = 25$) were based on self-reported mental health outcomes rather than (self-reported) clinical assessments or prescription data.

3.9. Meta-analytical results

3.9.1. Depression and neighborhood environment

Forty-two neighborhood social environment-depression associations were reported across 19 studies (Table 2), but only neighborhood SES and social cohesion were consistently studied at least five times. Pooling the five association estimates showed that composite neighborhood SES was negatively associated with levels of depression ($p = 0.007$), while the single neighborhood SES showed a null association with levels of depression ($p = 0.479$) based on 14 associations. The neighborhood social cohesion ($p = 0.463$) was also found to be insignificantly related with depression based on nine pooled associations.

Urbanicity was positively related with levels of depression ($p = 0.012$) based on pooling five reported associations. However, the association between available green spaces and depression was found to be insignificant ($p = 0.647$) based on seven associations. Statistically insignificant were the pooled associations of walkability ($p = 1.000$) based on seven associations and access to services ($p = 0.299$) based on seven associations.

3.9.2. Anxiety and neighborhood environment

Ten associations were reported between neighborhood environments and anxiety. However, these environments (i.e., neighborhood SES, residential stability, available green spaces, proximity to roadways, urbanicity) were all reported in less than five of the reviewed studies. In turn, this prevented meta-analysis of these specific associations.

3.9.3. Common mental disorder and neighborhood environment

The associations between neighborhood social, built environment, and common mental disorder were reported in too few studies to allow the performance of a meta-analysis. We observed a non-significant pooled association between available types of green spaces and common mental disorder across ten associations ($p = 1.000$). A paucity of studies preventing meta-analysis was also the case for other natural environmental characteristics such as available green spaces and the quality of green and blue spaces.

3.9.4. Pooled mental disorders and neighborhood environment

Pooling the 14 longitudinal associations of the three mental health outcomes (i.e., depression, anxiety, and common mental disorder), we found composite neighborhood SES was negatively associated with levels of pooled mental disorders ($p = 0.002$), while neighborhood urbanicity was positively associated with levels of pooled mental disorders ($p = 0.005$). Environments such as single neighborhood SES ($p = 0.828$), social cohesion ($p = 0.463$), available types of green spaces ($p = 1.000$), available green spaces ($p = 0.422$), walkability ($p = 1.000$), and

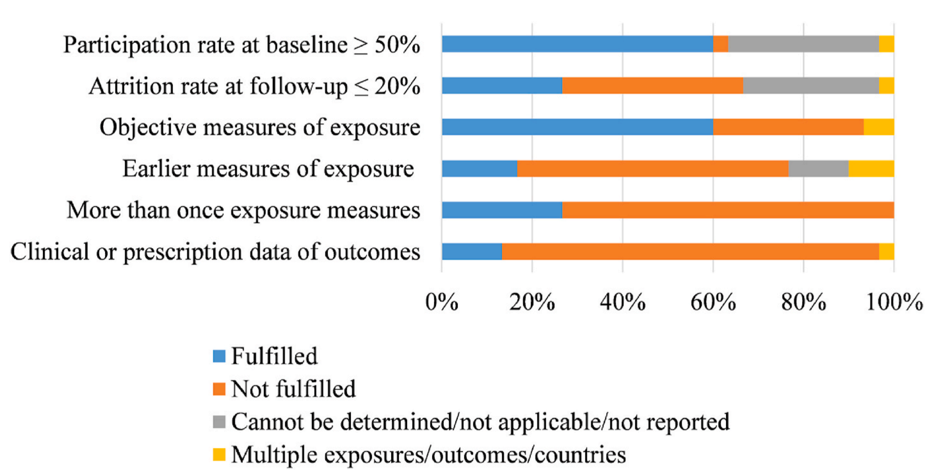

Fig. 2. Risk of bias in the included studies.

Table 2
Results of the meta-analysis on longitudinal associations between neighborhood environmental exposures and mental health outcomes.

Environmental exposure	Depression					Anxiety					Common mental disorder					Pooled mental disorders				
	N	Ø	P	*p*-value	D	N	Ø	P	*p*-value	D	N	Ø	P	*p*-value	D	N	Ø	P	*p*-value	D
Composite SES	**3**	**2**	**0**	**0.007**	**N**	1	1	0	–	–	–	–	–	–	–	**4**	**3**	**0**	**0.002**	**N**
Single SES	2	9	3	0.479	Ø	0	3	0	–	–	1	0	0	–	–	3	12	3	0.828	Ø
Disorder and nuisance	0	2	2	–	–	–	–	–	–	–	–	–	–	–	–	0	2	2	–	–
Residential stability	1	1	0	–	–	1	0	0	–	–	–	–	–	–	–	2	1	0	–	–
Demographic heterogeneity	0	1	0	–	–	–	–	–	–	–	–	–	–	–	–	0	1	0	–	–
Social cohesion	1	8	0	0.463	Ø	–	–	–	–	–	–	–	–	–	–	1	8	0	0.463	Ø
Violence	0	2	0	–	–	–	–	–	–	–	–	–	–	–	–	0	2	0	–	–
Safety	0	4	0	–	–	–	–	–	–	–	–	–	–	–	–	0	4	0	–	–
Trust	0	1	0	–	–	–	–	–	–	–	–	–	–	–	–	0	1	0	–	–
Available types of green spaces	0	1	0	–	–	–	–	–	–	–	0	10	0	–	1.000	0	11	0	1.000	Ø
Available green spaces	1	6	0	0.647	Ø	0	1	0	–	–	1	3	0	–	–	2	10	0	0.422	Ø
Quality of green spaces	–	–	–	–	–	–	–	–	–	–	0	1	0	–	–	0	1	0	–	–
Blue spaces	–	–	–	–	–	–	–	–	–	–	0.5	0.5	0	–	–	0.5	0.5	0	–	–
Aesthetic qualities	0	1	0	–	–	–	–	–	–	–	–	–	–	–	–	0	1	0	–	–
Proximity to roadways	0	0	1	–	–	0	0	1	–	–	–	–	–	–	–	0	0	2	–	–
Urbanicity	**0**	**2**	**3**	**0.012**	**P**	0	1	1	–	–	–	–	–	–	–	**0**	**3**	**4**	**0.005**	**P**
Walkability	0	7	0	1.000	Ø	–	–	–	–	–	–	–	–	–	–	0	7	0	1.000	Ø
Access to services	1.5	5.5	0	0.299	Ø	–	–	–	–	–	–	–	–	–	–	1.5	5.5	0	0.299	Ø
Land use mix	0	2	2	–	–	–	–	–	–	–	–	–	–	–	–	0	2	2	–	–
Population density	0	1	2	–	–	–	–	–	–	–	–	–	–	–	–	0	1	2	–	–

Abbreviations: N = negative association; Ø = null association; P = positive association; D = direction of the association in accordance with the meta-analysis.

access to services ($p = 0.299$) were non-significant.

3.10. Sensitivity analyses

The reported pooled association estimates between neighborhood environments and mental health outcomes passed several sensitivity tests. The findings remained similar with weights based on article quality and sample size and without weighting (Supplementary Table S8).

4. Discussion

4.1. Principal findings

Our systematic review and meta-analysis of 30 studies assessed possible longitudinal associations between neighborhood social, natural, and built environments and adults' mental health. Our results provided indicative evidence that composite neighborhood SES was negatively associated with levels of depression and pooled mental disorders. By contrast, neighborhood urbanicity was positively associated with levels of depression and pooled mental disorders, which remained in the sensitivity analyses. There was no evidence that natural neighborhood environmental characteristics, including green and blue spaces, were significantly associated with any assessed mental health outcome. Of note, the included studies were predominantly from developed countries. Furthermore, given the marked heterogeneity in study designs and how neighborhood environmental exposures were operationalized, confidence in the resulting pooled estimates must be limited.

4.2. Explanation of findings and available evidence

In line with our results, Richardson et al. (2015) found neighborhood SES was negatively associated with depression among adolescents and adults in high-income countries. Similarly, in Barnett et al. (2018), neighborhood SES was inversely associated with depression in older adults. This association could suggest that people living in low-level SES neighborhoods are more likely to experience higher risks for mental illness due to the presence of more stressors (e.g., crime, noise, disorder), and fewer stressor-combating resources (e.g., health clinics, social trust, cohesion). Our meta-analytical results showed that composite neighborhood SES was negatively associated with levels of depression and pooled mental disorders. By contrast, neighborhood SES operationalized through a single measure (e.g., income, education, wealth) showed a null association with any mental health outcome. Such a difference may be ascribed to different measurements of neighborhood SES (Zhang-Salomons et al., 2006). However, consensus on the conception and measurement of SES is lacking (Bollen et al., 2001; Lian et al., 2016).

We also found that urbanicity was positively associated with depression and pooled mental disorders. This finding is consistent with Peen et al. (2010), who found that the pooled prevalence of psychiatric disorders in high-income countries was higher in urban areas than in rural ones. Possible explanations include social stress caused by crowding (Moore et al., 2003), excessive competition (Hiremath, 2021), and social isolation (Mckenzie, 2008) is more widespread in urbanized areas, putting urban residents at greater risk for mental disorders (Peen et al., 2010).

According to our meta-analysis, social cohesion showed null associations with all assessed mental health outcomes. These results could be because almost all included studies measured respondents perceived social cohesion and self-reported mental health, which are likely subject to reporting bias (Yamaguchi et al., 2019). Alternatively, the age of participants might be a factor. Participants were 45 years or older in the included studies, but younger adults may benefit more from neighborhood cohesion (Robinette et al., 2013). It was speculated that older adults might rely more on close networks (e.g., family members) and less on perceived support from neighbors (Robinette et al., 2013), resulting in neighborhood social cohesion having limited effects on older adults' mental health.

Similarly, available green spaces were not associated with mental health outcomes. However, rather than the amount of green space, mental health benefits may arise through the quality of green space (e.g., aesthetics, accessibility, and usability) (Zhang et al., 2017), as several cross-sectional studies have suggested (Mears et al., 2020; Ngom et al., 2016; Tan et al., 2019). Health-supportive effects of neighborhood green spaces may also be stronger for specific population groups. For example, older people might spend more time in their residential neighborhoods and interact more with their surrounding green spaces than the working-age population (Pun et al., 2018; Roberts et al., 2020).

4.3. Strengths and limitations

Our study has several strengths. This review is the most comprehensive available in terms of multiple neighborhood environments and incorporates the most recent longitudinal findings. Furthermore, our review examined more mental health outcomes, individually and jointly, than other reviews in this domain (Barnett et al., 2018; Rautio et al., 2018; Richardson et al., 2015). Another strength is expanding the narrative summary by use of individually conducted meta-analyses for multiple social, natural, and built environmental characteristics. Our quality assessment found that the included studies were rated at a maximum as of moderate risk of bias, which increased the confidence in the reported pooled associations.

However, this review was also subject to several limitations. First, we could only conduct meta-analyses for eight neighborhood environmental characteristics because some aspects were assessed with comparable exposure-outcome combinations insufficiently often. Second, we only incorporated studies published in the English language. We acknowledge that we possibly missed relevant findings published in other languages and the grey literature. Third, we deviated from the PRISMA guidelines as the publications were only selected and screened by the first author. However, as shown elsewhere, study screening by a single person leads to negligible selection bias (Waffenschmidt et al., 2019). Fourth, many of the environment variables can be measured in multiple ways. For example, SES is a multidimensional concept (Hajat et al., 2021), and there is no consensus on how to best conceptualize and operationalize it (Bollen et al., 2001; Lian et al., 2016). Even though we acknowledged this lack of consensus by means of considering SES twofold (i.e., measures based on a single variable and composite scores), we cannot exclude the possibility that our approach led to some inconsistencies. Similarly, urbanicity was measured differently across studies. Here, we defined urbanicity as built-up areas (e.g., residential, industrial, and commercial areas) and transportation infrastructure. Again, we cannot rule out that different operationalizations may have affected the meta-analytical results. Fifth, we were unable to quantify the pooled effect size through the random-effects model due to pronounced study heterogeneity in terms of study design and numerous neighborhood environments, but our meta-analytical approach overcame the heterogeneity between the studies and provided, though less strong, quantitative evidence rather than narrative analysis. Sixth, the included studies varied in terms of their covariate adjustment level. Thus, we cannot exclude that this issue translated further into the estimates of our meta-analytical pooling. Lastly, related to the pronounced study heterogeneity, we were unable to carry out stratified meta-analyses (e.g., U.S. vs. Europe, urban vs. rural areas).

4.4. Implications for future progress

To advance our understanding of how neighborhood environments were associated with mental health, there are at least eight conceptual and methodological research priorities for future studies. First, only a few studies have applied a life course perspective (Kuh et al., 2003) due to a limited number of follow-up waves. However, a substantial proportion of mental disorders in adults originate early in life (e.g., childhood and adolescence), suggesting that adult mental illness can be an extension of juvenile mental illness (Kessler et al., 2007; Kieling et al., 2011; Kim-Cohen et al., 2003). Additionally, living in disadvantaged neighborhoods during childhood and adolescence may have long-lasting adverse effects on mental health later in life (Elovainio et al., 2020). In turn, omitting early life exposure may bias the relationship between neighborhood environment and adults' mental health. Thus, it is recommended that future research closely examines the effects of long-term neighborhood exposures.

Second, most studies only captured the neighborhood exposure at baseline. This practice is questionable because environmental settings may change dynamically over the follow-up durations and assessing environments only at a single time point creates the possibility for substantial measurement errors. For example, as shown elsewhere, neighborhood green spaces can shrink due to rapid urbanization processes (Yang et al., 2017). Moreover, considerable numbers of people change their residential neighborhoods over time. Additionally, there is increasing evidence that omitting exposures along residential histories may cause the underestimation of neighborhood effects (Hagedoorn and Helbich, 2021). Therefore, future studies are advised to incorporate time-varying environmental data along people's relocation trajectories into their research (Helbich, 2018; Pearce et al., 2018).

Third, effect sizes of neighborhood-based exposures are typically small, requiring large sample sizes to observe such effects. Furthermore, some included studies were likely statistically underpowered (Dzhambov, 2018; Mair et al., 2015; Murayama et al., 2015; O'Donnell et al., 2015). The need for large sample sizes and adequate statistical analysis highlights the need for more extensive future (multi-site) studies.

Fourth, there is no universally accepted standard for delineating the health-influencing neighborhood context. The use of different neighborhood boundaries (e.g., concentric or street network-based buffers or administrative units) and sizes may produce inconsistent results (Flowerdew et al., 2008; Schuurman et al., 2007). Progress can be achieved by using appropriate methodologies in assessing exposures and delineating the geographical health-influencing context (Helbich et al., 2021). Furthermore, the included studies only assessed people's residential living environments as exposure locations. However, while the home location is a crucial anchor point in individual's daily lives, individuals experience numerous out-of-home exposures while participating in such daily activities as work (Helbich, 2018). Future studies are recommended to incorporate these non-residential activity locations allowing more accurate capture of individual-level exposures.

Fifth, some studies assessed neighborhoods subjectively (Baranyi et al., 2019; Weimann et al., 2015), while others used objective measurements (Liu et al., 2021; Tarkiainen et al., 2021). However, objective and subjective assessments may not necessarily align well. Future studies should also investigate to what extent self-reported and objective assessment differ and whether such possible differences translate into differing assessments of environment-health associations.

Sixth, the included studies mainly assessed direct associations; a few also explored individual-level moderators, including age (Ruiz et al., 2018), year of residence (Murayama et al., 2015), and so forth. Only a few investigated neighborhood-level moderators (Fone et al., 2014; Pun et al., 2019) which are possibly of relevance to explain differences in mental health-environment associations.

Seventh, all the included studies were observational study designs due to practical and ethical concerns with experimental studies (for exceptions see Leventhal and Brooks-Gunn (2003) and Xie et al. (2022)). In order to address self-selection issues and strengthen causal inference in future studies, implementation of natural experiments is recommended (Morgan and Winship, 2015).

Finally, the included studies were primarily conducted in developed countries, which limits the transferability of our findings to developing countries. We recommend that future studies also focus on low- and middle-income countries, particularly those in the Global South, as such countries typically face distinct urban morphologies, urbanization patterns, and cultural settings.

5. Conclusion

The present systematic review of longitudinal studies supported by meta-analysis provided the most current and robust evidence that composite neighborhood SES was negatively associated with depression and pooled mental disorders. By contrast, neighborhood urbanicity was positively associated with depression and pooled mental disorders. Other natural environmental exposures (e.g., green and blue spaces) showed null associations. However, these findings stemmed primarily from developed country contexts, and comparability across the studies was limited.

To advance the evidence base, future research priorities should employ a life course perspective, implement time-varying environmental data, use comparable methodologies to assess neighborhood exposures, incorporate non-residential exposures along daily activities, and explore effect modifiers at the neighborhood level. All reviewed studies were observational, given the ethical context and to strengthen causal inference in future studies, we advise conducting natural experiments, ideally in developed as well as in low- and middle-income countries.

CRediT authorship contribution statement

Yuwen Sui: Conceptualization, Methodology, Analysis, Data curation, Resources, Writing - Original draft, Visualization, Funding acquisition. Dick Ettema: Supervision, Writing - Reviewing and Editing. Marco Helbich: Supervision, Conceptualization, Writing - Reviewing and Editing.

Funding

Yuwen Sui was supported by a grant from the China Scholarship Council (No. 202004910396). The funder had no influence on the study design, data collection and analysis, interpretation, or article writing.

Declaration of competing interest

The authors declare that they have no competing interests.

Data availability

Data will be made available on request.

Acknowledgements

We thank the reviewers for their constructive comments.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2022.102893.

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