# The economics of nature's healing touch: A systematic review and conceptual framework of green space, pharmaceutical prescriptions, and healthcare expenditure associations

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## Abstract

Green spaces play a crucial role in promoting sustainable and healthy lives. Recent evidence shows that green space also may reduce the need for healthcare, prescription medications, and associated costs. This systematic review provides the first comprehensive assessment of the available literature examining green space exposure and its associations with healthcare prescriptions and expenditures. We applied Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines to search MEDLINE, Scopus, and Web of Science for observational studies published in English through May 6, 2023. A quality assessment of the included studies was conducted using the Office of Health Assessment and Translation (OHAT) tool, and the Grading of Recommendations, Assessment, Development, and Evaluations (GRADE) assessment was used to evaluate the overall quality of evidence. Our search retrieved 26 studies that met the inclusion criteria and were included in our review. Among these, 20 studies (77% of the total) showed beneficial associations of green space exposure with healthcare prescriptions or expenditures. However, most studies had risks of bias, and the overall strength of evidence for both outcomes was limited. Based on our findings and related bodies of literature, we present a conceptual framework to explain the possible associations and complex mechanisms underlying green space and healthcare outcomes. The framework differs from existing green space and health models by including upstream factors related to healthcare access (i.e., rurality and socioeconomic status), which may flip the direction of associations. Additional research with lower risks of bias is necessary to validate this framework and better understand the potential for green space to reduce healthcare prescriptions and expenditures.

## Graphic Abstract

## 1. Introduction

Healthcare expenditures are rapidly increasing across the world. For instance, global expenditures were \$9 trillion in 2020, up from \$7.8 trillion in 2017. Expenditures now constitute 10.8% of the global gross domestic product (GDP) (World Health Organization, 2020; Anwar, Madni and Yasin, 2021). The COVID-19 pandemic triggered a further cost surge (Micah *et al.*, 2023). Simultaneously, environmental degradation, indoor and outdoor air pollution, urban heat islands, global climate change, and rapid urbanization have caused concerning impacts on human health and well-being (Almetwally, Bin-Jumah and Allam, 2020; Palinkas and Wong, 2020; Piracha and Chaudhary, 2022). Many of these health conditions are leading causes of governmental and private healthcare expenditures (Chapel et al., 2017; Dieleman et al., 2016; Lassman et al., 2017). Furthermore, negative environmental changes cause disproportionate burdens on traditionally underserved populations in higher-income countries but also many residents of low- and middle-income countries (LMICs), considering their environmentally vulnerable situations, low per capita incomes, and "fragile" healthcare systems (Hanson *et al.*, 2022). To ensure healthy lives, promote well-being, and pursue global initiatives such as the United Nations Sustainable Development Goal-3 (SDG-3), which is focused on "good health and well-being," it is vital to focus on healthy, livable environments along with proper economic and healthcare support.

Green spaces such as parks, forests, and tree-lined streets are central to sustainable and healthy lives (Martin *et al.*, 2020). However, they have been less explored in environmental and health studies than air pollution and other harmful exposures (Anwar, Madni and Yasin, 2021). Growing evidence points to strong, positive relations between green space exposure and physical, psychological, and social health and well-being (Yang *et al.*, 2021). Higher levels of exposure to green space have also been related to reduced risk of blood pressure (Zhao *et al.*, 2022), obesity (Teixeira *et al.*, 2021), cardiovascular disease (Liu *et al.*, 2022), diabetes (Ccami-Bernal *et al.*, 2023), neurodegenerative disease (Besser, 2021), and birth-fetal outcomes (Zhan *et al.*, 2020). Meanwhile, green space exposure improves mental health, reducing symptoms of stress, anxiety, depression, emotional distress, and negative mood (Bratman *et al.*, 2019). A growing body of literature has also suggested that green space may increase levels of several forms of physical activity, such as walking, jogging, and cycling (Noseworthy *et al.*, 2023), leading to better health overall and less need for healthcare services. Therefore, green space has a solid potential to be associated with fewer healthcare expenditures and prescriptions.

In addition to the residential settings, several studies have been conducted with hospital patients to investigate the healthcare implications of green space exposure. An early study by Ulrich found that cholecystectomy patients with a window view of trees and green space, compared to another hospital wall, required shorter postoperative hospital days, fewer potent analgesics, and fewer negative evaluative comments from caregivers (Ulrich, 1984). Accelerated recovery with green space exposure has also been observed among patients in a rehabilitation center (Raanaas, Patil and Hartig, 2012), surgical patients (Park and Mattson, 2009), individuals having schizophrenia (Henson *et al.*, 2020), women with post-cesarean section (Wang, Kuo and Anthony, 2019), and pediatric patients (Said *et al.*, 2005).

Researchers have also examined nature prescriptions as a public health intervention (Carpenter, 2013; Koselka *et al.*, 2019; Kondo *et al.*, 2020). Recent meta-analyses and systematic reviews report that nature prescription programs led to clinically meaningful reductions in systolic and diastolic blood pressure, depression, anxiety, and inflammation, as well as increases in psychological well-being and physical activity (Adewuyi *et al.*, 2023; Nguyen *et al.*, 2023). This evidence further supports the possibility that green space exposure may be associated with fewer healthcare prescriptions and expenditures.

Recent studies have directly examined associations between green space exposure, healthcare expenditures, and related outcomes. For instance, healthcare costs were examined concerning green space availability by (Becker *et al.*, 2019; Sato *et al.*, 2019; Astell-Burt *et al.*, 2021; Cerletti *et al.*, 2021; Van Den Eeden *et al.*, 2022), among others. A related body of literature has examined whether green space exposure is associated with prescription medications, such as for cardiovascular disease (Aerts, Nemery, *et al.*, 2020), gastrointestinal illness (DeFlorio-Barker *et al.*, 2017), and mental health conditions (Aerts *et al.*, 2022). This growing volume in research creates an opportunity and need to synthesize the available evidence on green space exposure and its associations with healthcare prescriptions and expenditures. Few reviews on this topic are available, but these do not include recent studies nor provide systematic approaches (Wolf *et al.*, 2015; Chen, 2020; Busk *et al.*, 2022).

The current systematic review aims to summarize and evaluate the existing evidence on associations of healthcare prescriptions and expenditures with green space exposure. We did not seek to provide a comprehensive overview of green space exposure and healthcare utilization, which would have involved outcomes less clearly linked with health status (i.e., screenings and elective procedures) as well as inpatient care encounters that have been summarized elsewhere (Trøstrup *et al.*, 2019; Chi, Gutberg and Berta, 2020; Sal Moslehian *et al.*, 2023). Instead, we limited our review to two possible healthcare outcomes of green space exposure (pharmaceutical prescriptions and expenditures) with narrowly defined outcomes and keywords to retrieve relevant records. Our central research question was, "To what extent is green space exposure associated with healthcare expenditures and medical prescriptions?" To answer this question, we followed a systematic review approach with assessments for study biases and overall quality of evidence. We then established a framework to explain the hypothesized associations between green space exposure and healthcare outcomes. Based on our findings and this framework, we highlighted potential research gaps and future study needs to assist researchers and healthcare policymakers understand this body of literature.

## 2. Methods

### 2.1. Study protocol

The systematic review was carried out according to the updated Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines (Page *et al.*, 2021). These incorporated four aspects: study identification, screening, eligibility, and included studies. The pre-developed protocol was registered at the International Prospective Register of Systematic Reviews database (PROSPERO, registered ID: CRD42023387404: https://www.crd.york.ac.uk/prospero/display_record.php?ID=CRD42023387404).

### 2.2. Eligibility criteria

Queries were developed based on the population, exposure, comparator, outcome, and study design (PECOS) framework. This approach ensured that the included articles complied with the research question and minimized the potential risk of bias in the review process (Hu *et al.*, 2021; Ricciardi *et al.*, 2022; Zare Sakhvidi *et al.*, 2023). The PECOS criteria for this review included:

#### *2.2.1. Population*

Studies focused on general human populations. Non-human studies were excluded. We did not restrict by geographic location, age group, gender, or socioeconomic characteristics.

#### *2.2.2. Exposure*

Studies with subjective or objective exposure to outdoor green space, including urban green space, parks, tree canopy, and forests, among others. Studies estimating the impact of green space with simulations (i.e., pictures, videos, or virtual reality) were excluded.

#### *2.2.3. Comparator*

Studies with populations exposed to higher versus lower levels of green space.

#### *2.2.4. Outcome*

Studies examining healthcare expenditures (i.e., out-of-pocket costs or total costs) or prescription medications (i.e., rates) attributable to individuals (i.e., per capita) or groups of people (i.e., the total of spending in a cohort or geographic unit) across any unit of time (i.e., per month, year, etc.). Health impact assessments or estimates of costs based on modeling studies were excluded.

#### *2.2.5. Study design*

Observational studies with a cross-sectional or cohort individual-level or ecological (area-level) study design were included to look at longer-term outcomes of green space exposure. We included both quantitative and mixed-method designs in our sample. Still, we excluded experimental studies, which may represent shorter-term (i.e., hours or days) green space exposures, and studies that only used qualitative methods.

Inclusion criteria also included original peer-reviewed articles published by May 6, 2023, with full-texts available in English. Exclusion criteria included peer-reviewed articles not describing original research (e.g., reviews, editorials, commentaries, letters to the editor, and case reports), unpublished theses and data, duplicate studies, books, and conference papers.

### 2.3. Search queries

The search queries for the current review were adapted for three electronic databases, including MEDLINE (via PubMed), Scopus (Elsevier), and Web of Science. We included search terms for 'green space exposure' and 'healthcare prescriptions and expenditures' as detailed in Table S1. In our search, we used OR between exposure and outcome keywords while joining exposures with outcomes using AND. Example keywords for 'green space exposure' included built environment, urban environment, urbanization, green space, greenness, greenery, normalized difference vegetation index, NDVI, MSAVI, SAVI, vegetation, park, natural environments, land use, land cover, exposure to nature, nature exposure, and nature contact selected from prior reviews (de Keijzer, Bauwelinck and Dadvand, 2020; Zhang *et al.*, 2020; Vella-Brodrick and Gilowska, 2022; Buczyłowska *et al.*, 2023; Zare Sakhvidi *et al.*, 2023). Example keywords for 'healthcare prescriptions and expenditures' included healthcare expenditure, healthcare cost, healthcare saving, healthcare spending, prescription, medication, Medicare spending, and prescribing, based on past work (Taylor *et al.*, 2015; Sato *et al.*, 2019; Kabaya, 2020; Anwar, Madni and Yasin, 2021; Cerletti *et al.*, 2021;

Aerts *et al.*, 2022). A manual search was also conducted on the relevant articles in the keyword search to identify pertinent additional works. All searches were performed on May 6, 2023.

### 2.4. Study selection

After completing the keyword searches in the three databases, articles were imported into Rayyan (https://www.rayyan.ai/), an intelligent research collaboration platform. Two reviewers (MMP, MB) independently performed the article screening based on titles and abstracts after removing the duplicates. The selected articles from the title and abstract screening were considered for full-text screening. During the title, abstract, and full-text screening, studies were included only when they met the predefined inclusion criteria. The reviewers resolved conflicts through discussion and excluded articles with reasons if the articles did not match the inclusion criteria.

### 2.5. Data extraction

Two reviewers (MMP, MB) performed data extraction and cross-checked independently. A Google Sheet was used to collect and tabulate data from the included articles. The extracted data had the characteristics of the study and participants, a description of the exposure and outcome, statistical analyses, and main findings. Study characteristics encompassed the authors' name, publication year, and study design. Participant characteristics covered the study area, sample size, population types, and recruitment strategies. Exposure description considered the exposure time period(s), data source(s), and exposure type(s). Outcome description included healthcare expenditure or prescription type(s) and data source(s). Along with the main findings, the reviewers extracted the interpretation of the main results and the adjusted variables used in the analyses. In the case of missing data, the reviewers contacted the corresponding authors.

Two reviewers (MMP, MB) also independently extracted the reported associations, such as odds ratios (OR) and relative risks (RR), with corresponding confidence intervals (CIs) to determine the effect sizes, directions, and magnitudes of associations. Finally, one reviewer (MHEMB) extracted data on how contextual factors previously shown to affect the green space and health relationship (Rigolon *et al.*, 2021; Browning *et al.*, 2022) modified the direction or strength of the reported associations. These included urbanicity (i.e., urban-rural classifications, population density, or housing density) and socioeconomic status (i.e., household income and neighborhood disadvantage).

Considering the diverse green space exposure indicators, buffer sizes, and studied health outcomes within the scope of our review, we determined meta-analyses were unsuitable for the extracted data. Consequently, a narrative synthesis of evidence was performed.

### 2.6. Risk of bias assessment

We evaluated the risk of bias in the included studies using the Office of Health and Assessment Translation (OHAT) risk of bias (RoB) tool for human and animal studies (Cano-Sancho *et al.*, 2019). This tool has been previously employed in review articles examining the associations between environmental exposures (including green spaces) and health outcomes (Buczyłowska *et al.*, 2023; Cao *et al.*, 2023). Three main elements were considered: exposure bias, outcome bias, and confounding bias. Four other methodological criteria were assessed: selection bias, attrition/exclusion bias, selective reporting bias, and conflict of interest. Each of these domains was graded as "Definitely low," "Probably low," "Probably high," or "Definitely high" in alignment with established guidelines (Table S2).

Studies were categorized into three distinct tiers based on the OHAT RoB tool. Tier 1 comprised studies with "definitely low" and "probably low" RoB, while Tier 3 encompassed studies with "definitely high" or "probably high" RoB. Studies that did not meet the criteria mentioned above were placed in Tier 2 (Cao *et al.*, 2023). Two independent reviewers (MMP, MB) assessed the RoB based on the criteria. Any disagreement was resolved through discussion with a third reviewer (MHEMB).

For the confounding bias domain, we categorized potential confounding variables into two tiers. ***Tier 1*** encompassed the most important confounders: age, gender, and socioeconomic status (SES). Following previous research (Mueller *et al.,* 2022), ***Tier 2*** comprised other potentially pertinent confounders, such as air pollution and physical activity levels. We recognized these are likely also in the causal pathways between green space exposure, health, and healthcare outcomes and, therefore, should also be included in mediation analyses if controlled for in an individual study.

### 2.7. Evaluation of quality of evidence assessment

We adopted the Navigation Guide quality of evidence tool, Grading of Recommendations, Assessment, Development, and Evaluations (GRADE) for the evaluation of the quality of evidence across studies, following previous studies (Lam *et al.*, 2021; Cao *et al.*, 2023; Haddad *et al.*, 2023). The quality of evidence was categorized into four levels: high, moderate, low, and very low. The tool integrates upgrades and downgrades to its initial ratings. Upgrades considered a large magnitude of effect, dose-response relationship, and confounding factors (Johnson *et al.*, 2014). Downgrades considered the risk of bias, indirectness, inconsistency, imprecision, and publication bias (Johnson *et al.*, 2014). Assessing the risk of bias in the evidence seeks appropriate eligibility criteria, measurement of exposure and outcome, control of confounding, and follow-up (Guyatt, Oxman, Vist, *et al.*, 2011). Indirectness in the evidence measures the differences in study populations, exposures, and outcomes of the target population (Guyatt, Oxman, Kunz, Woodcock, Brozek, Helfand, Alonso-Coello, Falck-Ytter, *et al.*, 2011). Inconsistency considers variation in point estimates, lack of overlapping CIs, statistical heterogeneity, and proportion of variation ($I^2$) (Guyatt, Oxman, Kunz, Woodcock, Brozek, Helfand, Alonso-Coello, Glasziou, *et al.*, 2011). Imprecision refers to a small number of studies (<3), small sample sizes, wide CIs or contradictory associations of the same exposure-outcome pair (Guyatt, Oxman, Kunz, Brozek, *et al.*, 2011). However, considering the limited studies available, we could not conduct a publication bias assessment (Hanka, 1994).

Ultimately, the overall body of evidence for prescriptions and expenditures was independently rated as “high,” “moderate,” “low,” or “very low.” Initially, all studies were considered to have “moderate” quality (Lam *et al.*, 2016). Following this, we applied predefined criteria, which allowed us to upgrade or downgrade the evidence based on specific considerations. Here, 0 was considered for no change in ratings from the initial quality, while -1 or -2 were for downgraded ratings. +1 or +2 were used for upgraded ratings (Balshem *et al.*, 2011). Two reviewers (MMP and MB) independently rated the evidence, and consensus resolved disagreements. The assessment guidelines with all rationale and judgments are presented in Tables S3-S4.

### 2.8. Strength of evidence assessment

Our assessment of the strength of the evidence used the Navigation Guide framework, a systematic approach for separately evaluating human and non-human studies before combining their overall strength (Lam *et al.*, 2016). Ratings were based on the following criteria: (1) Quality of body of evidence (i.e., the rating from the previous step), (2) Direction of effect, (3) Confidence in effect (likelihood that a new study could change our conclusion), and (4) Other compelling attributes of the data that may influence certainty. The final ratings fell into one of the following categories: "sufficient evidence of benefits," indicating a robust body of evidence supporting beneficial effects; "limited evidence of benefits," suggesting the presence of evidence but with limitations; "inadequate evidence of benefits," signifying a lack of sufficient data to conclude benefits; and evidence of benefits absence," indicating a lack of substantial evidence supporting benefits. These assessments underwent a refinement process through discussions and consensus-building among all authors. Detailed criteria for these adjustments are outlined in Table S5.

## 3. Results

### 3.1. Identified articles

Initially, 5,303 study records were identified from the three databases (Figure 1). After removing duplicates, 3,408 unique articles remained. After evaluating the titles, abstracts, and full texts, 26 studies met the inclusion criteria and were included in the review.

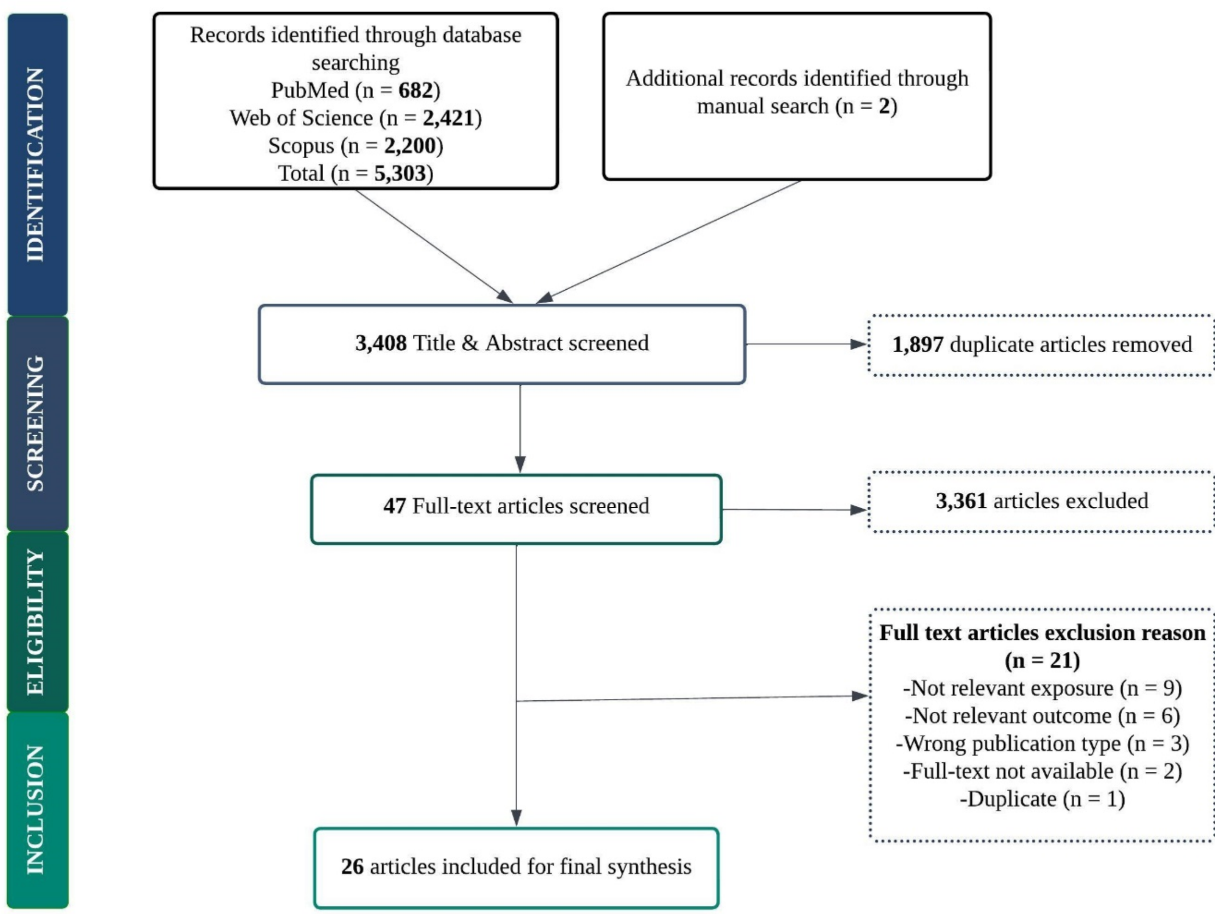


**Figure 1.** Flow diagram of study selection.

### 3.2. Study characteristics

Figure 2 summarizes the characteristics of the included studies. Reasons for excluded studies at the full-text stage are provided in Table S6.

Most of the included studies took place in Europe (50%). Regarding individual countries, the highest number of studies came from the U.S. (n = 7), followed by Belgium (n = 4), Scotland (n = 3), and Australia (n =2). Two studies were based on data from multiple countries.

Regarding study design, 16 (62%) were ecological (area-level) and 9 were individual-level, including 7 (27%) cross-sectional studies and 3 (12%) cohort studies (Figure 3).

| | N (%) |
|---|---|
| **Study location** | |
| Europe | 13 (50%) |
| USA | 7 (27%) |
| Asia | 2 (8%) |
| Australia | 2 (8%) |
| Multi-country | 2 (8%) |
| **Population** | |
| Adults | 18 (69%) |
| Older people | 5 (19%) |
| Children | 1 (4%) |
| ICU Patient | 1 (4%) |
| Not Reported | 1 (4%) |
| **Study design** | |
| Ecological | 16 (62%) |
| Cross-sectional | 7 (27%) |
| Cohort | 3 (12%) |
| **Health outcomes** | |
| Prescriptions | 13 (50%) |
| Expenditures | 11 (42%) |
| Prescriptions & Expenditures | 2 (8%) |

| | N (%) |
|---|---|
| **Health outcomes data source** | |
| Electronic Health Records | 15 (58%) |
| Questionnaire | 6 (23%) |
| Census dataset | 2 (8%) |
| Others | 3 (12%) |
| **Specific measurements of health outcomes** | |
| Antidepressant prescriptions | 9 (32%) |
| Cardiovascular disease prescriptions | 2 (8%) |
| Hypertension prescriptions | 2 (8%) |
| Asthma prescriptions | 1 (4%) |
| Mood disorder prescriptions | 1 (4%) |
| Total healthcare expenditures | 10 (38%) |
| Mental healthcare expenditures | 2 (8%) |
| Antidepressant medication costs | 1 (4%) |
| Cardiovascular prescribing costs | 1 (4%) |
| Emergency department visit costs | 1 (4%) |
| Hospitalization costs | 1 (4%) |
| Medical product expenditures | 1 (4%) |

Some studies utilized multiple methods that may cause the total percentages in the columns to exceed 100%.

**Figure 2.** Study characteristics (n = 26).

Eighteen studies reported on adult populations (≥18 years old), 5 reported on older adults (≥65 years old), one reported on children (6 to 17 years old), one reported on intensive care unit (ICU) patients without reported ages, and one did not report the population type. Of the total, 13 studies used census tracts, counties, or data zones (Scottish units similar to U.S. Census Block Groups) as the analysis unit. The other 12 studies used individual-level data from samples ranging in size from 476 to 5,189,303.

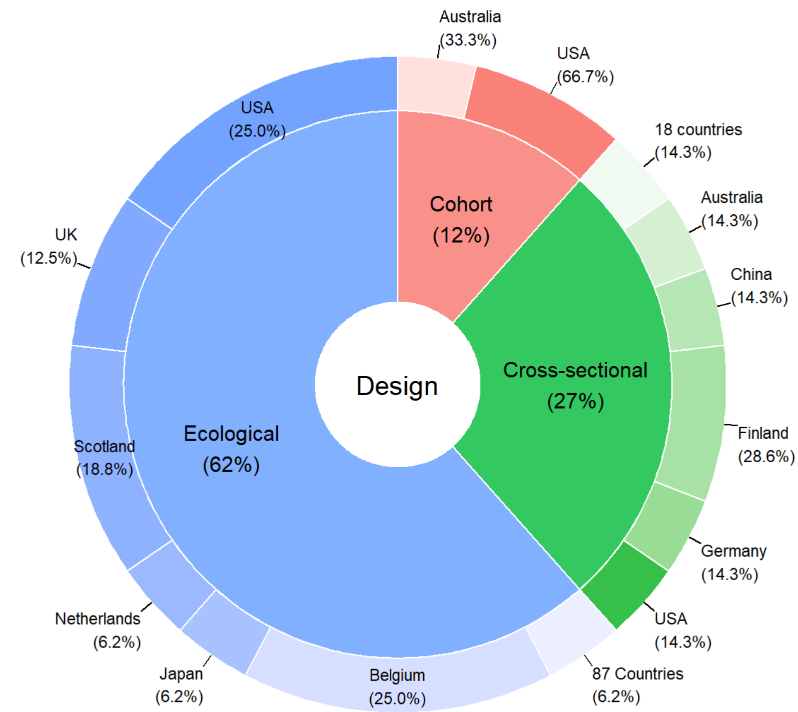


**Figure 3.** Geographical distribution of study designs (n = 26).

### 3.3. Green space exposure assessment

Studies included the availability of green space, accessibility of green space, and visits to green spaces (Figure 4). Availability was the most commonly assessed, with 23 (88%) articles utilizing this approach. Availability of green space was measured by indices such as the normalized difference vegetation index (NDVI), percentage of greenness coverage, and percent canopy cover (Table 1). Buffer sizes in which availability was measured ranged from 250-m (Van Den Eeden *et al.*, 2022) to 2-km (Roberts, Irvine and McVittie, 2021). Circular buffers were employed in most studies, but one study used centroid buffers (Astell-Burt *et al.*, 2021), and the remaining used polygonal buffers (Roberts, Irvine and McVittie, 2021). The most commonly utilized buffer sizes were 500-m and 1-km (Table 1). Higher proportions of green space availability (88.2%) were present in the ecological studies than in individual-level studies (Figure 5). Seven studies reported on accessibility to green space. Studies reported proximity to green space, access to park facilities (Sato *et al.*, 2019; Wali *et al.*, 2022) or green space views (Kohn *et al.*, 2013). Four studies examined visits to green space (White *et al.*, 2021; Buckley and Chauvenet, 2022; Turunen *et al.,* 2023; Zhang and Wu, 2022).

Eleven studies reported the temporal alignment between green space exposure and the outcome. Alignments ranged from one year (Taylor *et al.*, 2015; Helbich *et al.*, 2018) to six years in duration (Gidlow *et al.*, 2016). Of these, three studies reported exposure within the outcome time measurement (Aerts, Dujardin, *et al.*, 2020; Aerts *et al.*, 2022; Chi *et al.*, 2022), while one reported exposure after the outcome (Taylor *et al.*, 2015) (Table S7).

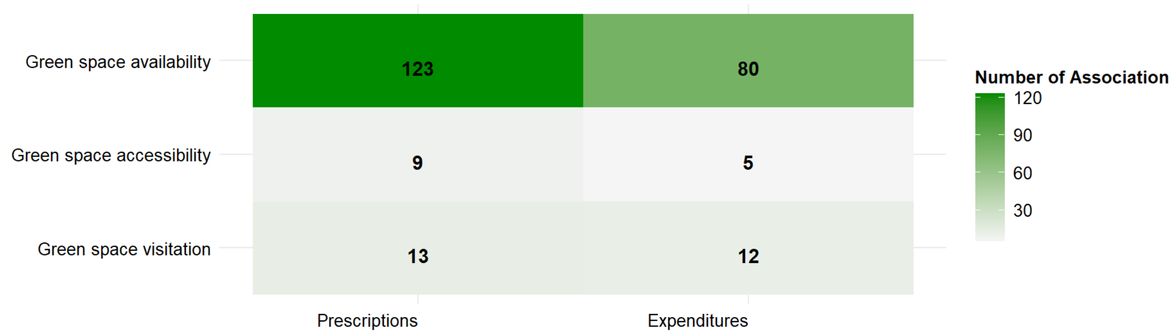


**Figure 4.** Counts of studies (n = 242) within articles (n = 26) by green space exposure measurement.

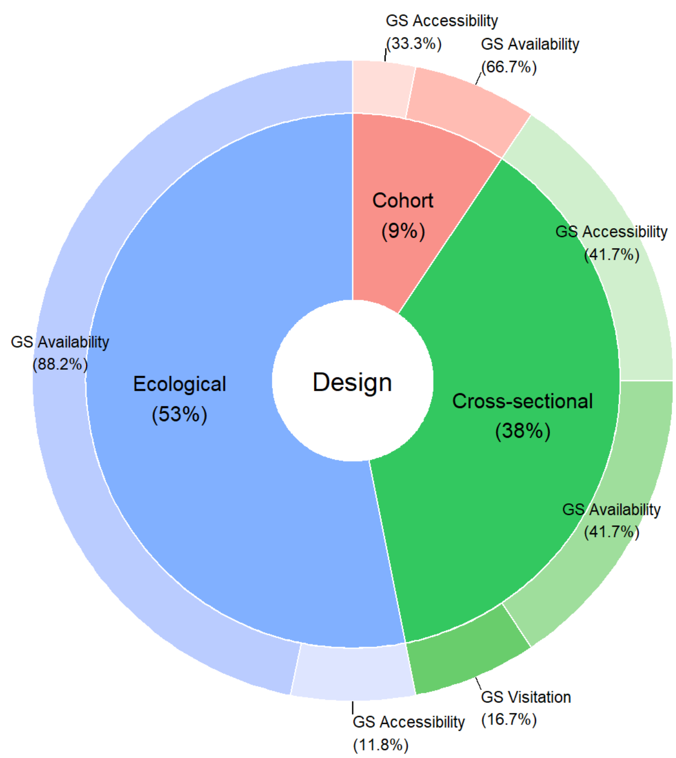


**Figure 5.** Shares of study designs by green space exposure measurement (n = 26).

**Table 1.** Measures of green space exposure in reviewed studies (n = 26).

| *Author* | *Exposure type* | *Exposure measure(s)* | *Buffer size (type)* | *Source* |
|---|---|---|---|---|
| (Aerts, Nemery, *et al.*, 2020) | Availability | Greenspace (Forest patch, Forest cover, Forest cover (buffer)) | 600m (Circular) | CORINE Land Cover (CLC) |
| (Aerts, Dujardin, *et al.*, 2020) | Availability | Grassland cover (%); Garden cover (%); Forest cover (%) | No | Land cover data (Belgian National Geographic Institute) |
| (Aerts *et al.*, 2022) | Availability | Greenspace cover (%): woodland, low green, garden, grassland | No | Land cover data (Belgian National Geographic Institute) |

| | | | | |
|---|---|---|---|---|
| (Anwar, Madni and Yasin, 2021) | Availability | Forest coverage | No | World Development Indicators (WDI) |
| (Astell-Burt *et al.*, 2021) | Availability | Total greenspace; Tree canopy; Open grass | 1.6 km (Centroid) | Land use data at 2-$m^2$ resolution (Pitney Bowes Ltd) |
| (Becker and Browning, 2021) | Availability | NDVI; | No | NDVI from satellite images (MODIS, 250-$m^2$ resolution);<br>National Land Cover Database (NLCD) |
| (Becker *et al.*, 2019) | Availability | Green land cover (Forest, Shrub, Grass, Urban vegetation) | No | NLCD |
| (Buckley and Chauvenet, 2022) | Visitation | Park visit; Greenspace visit | | Questionnaire |
| (Chi *et al.*, 2022) | Availability | Tree height, crown diameter, crown volume, canopy cover, leaf area index, | No | LiDAR data |
| (Gidlow *et al.*, 2016) | Availability | Natural environment (public green spaces, gardens, and blue spaces) | No | Generalized Land Use Database (GLUD) |
| (Helbich *et al.*, 2018) | Availability | Green space (%) | No | Dutch land use database |
| (Kabaya, 2020) | Availability, Accessibility | Overall forest coverage<br>Evergreen forest coverage<br>Deciduous forest coverage<br>Mixed forest coverage<br>Forest proximity score<br>Forest diversity score | No | Satellite image (MODIS, 250-$m^2$ resolution) |
| (Kohn *et al.*, 2013) | Accessibility | Windows views of nature | No | Electronic health records |
| (Maantay and Maroko, 2015) | Availability | Vacant and derelict land | No | Glasgow City Council's Development and Regeneration Services (DRS) |
| (Marselle *et al.*, 2020) | Availability, Accessibility | Public street trees; street tree abundance; species richness; spatial proximity of exposure; Street tree quantity | 100, 300, 500, and 1000 m (Circular) | City of Leipzig, Open street map |
| (McDougall *et al.*, 2021) | Availability | Public green space coverage, Total green space coverage | 800m, 1600m (Circular) | Ordnance Survey Open Map |
| (Okokon *et al.*, 2021) | Availability | Arable land, pastures, forests, green urban areas, herbaceous vegetation associations, and open spaces with little or no vegetation were designated as green areas, while sea, lakes, rivers, and wetlands were designated as blue areas within buffer zones of 300 m and 1 km around each home | 300m, 1km (Circular) | LULC Urban Atlas (European Environment Agency, Copenhagen, Denmark) |
| (Roberts, Irvine and McVittie, 2021) | Availability | Neighborhood greenspace; Greenspace with 2km buffer zone | 2km (Polygon) | Scottish Greenspace Map 2011 |
| (Rosenberger *et al.*, 2005) | Availability | Municipal Land, Public Land, Parks & Recreation Department | No | USDA |
| (Sato *et al.*, 2019) | Accessibility | Access to parks | No | DeLorrme MapMart, Ersi geographic information system data, Open Source Global Business Browser |
| (Taylor *et al.*, 2015) | Availability | Street tree | No | Greater London Authority |
| (Turunen *et al.*, 2023) | Availability, Accessibility | Amount of residential greenspace (%); Frequency of greenspace visits; Green view from window; | 1km (Circular) | LULC Urban Atlas (European Environment Agency, Copenhagen, Denmark) |
| (Van Den Eeden *et al.*, 2022) | Availability | Greenness (NDVI) | 250m, 500m, 1000m (Circular) | NDVI from satellite images (MODIS, 250-$m^2$ resolution) |
| (Wali *et al.*, 2022) | Accessibility | Access to parks | 1000m (Circular) | Questionnaire |
| (White *et al.*, 2021) | Availability, Accessibility | Residential greenness ; Frequency of visit to green space ; Nature connectedness | 1km (Circular) | Global Land Cover dataset (GlobeLand30);<br>Questionnaire |
| (Zhang and Wu, 2022) | Availability, Accessibility, Visitation | Amount of UGS; Demand for UGS activity; Supply of UGS activity; Total UGS; Amount of nearby UGS (perceived); Quality of UGS | 400m (Circular) | Satellite image (Landsat, 30-$m^2$ resolution);<br>Questionnaire |

Notes: LiDAR, light detection and ranging; MODIS, moderate resolution imaging spectroradiometer; NDVI, normalized difference vegetation index; USDA, U.S. Department of Agriculture (details on USDA dataset were unavailable); UGS, Urban Green Space

### 3.4. Outcome assessment

Thirteen of the studies reported only on prescriptions. Eleven reported only on healthcare expenditures, and two reported on prescriptions and expenditures.

Among studies on healthcare prescriptions, five (33%) reported on antidepressant prescriptions, three (20%) reported on anxiety, depression, or psychosis prescriptions, two (13%) on cardiovascular disease prescriptions, two (13%) on hypertension prescriptions, and one each (13%) on mood disorder (Chi *et al.*, 2022) and asthma prescriptions (Turunen *et al.*, 2023). Among studies on healthcare expenditures, 10 (66%) reported per-capita total healthcare costs, one reported on mental healthcare costs (Buckley & Cauvenet, 2022), and one each reported on costs of antidepressant prescriptions and cost of referrals for talking therapy (Astell-Burt *et al.*, 2021), costs per case of gastrointestinal illness (DeFlorio-Barker *et al.*, 2017), cardiovascular prescribing costs (Gidlow *et al.*, 2016), and total and sub-category costs including outpatient, inpatient, emergency room, and pharmacy (Van Den Eeden *et al.*, 2022), hospitalization costs (Kohn *et al.*, 2013) and health insurance expenditures (Zhang and Wu, 2022).

Various data sources were employed to measure health outcomes. Electronic health records (EHRs) were the most commonly used data sources. Six studies used questionnaires, while two used the Scotland Census dataset (Maantay and Maroko, 2015; Roberts, Irvine and McVittie, 2021), and one study each used the World Development Indicators (WDI) data (Anwar, Madni and Yasin, 2021), National Health Insurance (NHI) annual reports (Kabaya, 2020) and Greater London Authority data (Taylor *et al.*, 2015).

### 3.5. Associations between green space exposure and healthcare outcomes

Among the 242 associations identified in the review, 34% (n = 83) reported statistically significant (i.e., point estimates below 1.00, or p-value less than 0.05) negative (protective) associations of green space exposure on healthcare prescriptions or expenditures. Conversely, 25% (n = 61) reported estimates or p-values representing positive (harmful) associations of green space exposure on these outcomes. Less than one-half (n = 98, 45%) reported null associations (Figure 6).

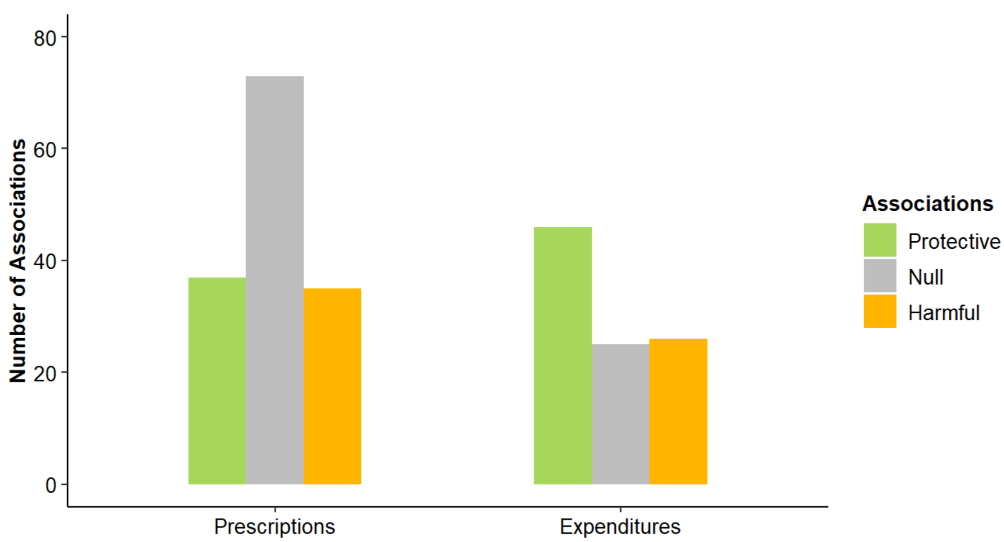

**Figure 6.** Direction and statistical significance of associations between green space exposure and healthcare outcomes (n = 242 associations across 26 articles).

#### *3.5.1. Healthcare prescriptions*

Fifteen (58%) studies reported associations between green space exposure and healthcare prescriptions (Table 2). Most (n = 10, 67%) reported green space availability was associated with reduced prescription rates, including antidepressant prescriptions (Taylor *et al.*, 2015; Helbich *et al.*, 2018; Marselle *et al.*, 2020; McDougall *et al.*, 2021; Roberts, Irvine and McVittie, 2021; Turunen *et al.*, 2023), mood disorder medication sales (Aerts *et al.*, 2022), cardiovascular medication sales (Aerts, Nemery, *et al.*, 2020), use of psychotropic medication (Roberts, Irvine and McVittie, 2021; Turunen *et al.*, 2023), and antihypertensive and asthma medication sales (Turunen *et al.*, 2023). One study reported that public green space coverage was associated with reduced antidepressant prescriptions (McDougall *et al.*, 2021). Also, one study reported that individuals who visited green spaces more than 3-times per week had lower antihypertensive and asthma medication rates (Turunen *et al.*, 2023). By contrast, three studies reported the opposite associations of green space availability, including one reporting total green space coverage in wider neighborhoods was associated with higher antidepressant medication rates (McDougall *et al.*, 2021), another reporting open grass was associated with higher antidepressant prescriptions (Astell-Burt *et al.*, 2021), and the last one showing higher tree density was associated with higher cardiovascular disease medications (Chi *et al.*, 2022).

Four studies examined effect modification by SES. Turunen *et al.* (2023) reported that the protective association of green space on psychotropic medication use was strongest among respondents with lower annual household incomes. Marselle *et al.* (2020) found that the protective associations of street tree density on antidepressants existed only for the lower SES group. Similarly, Chi *et al.* (2022) found that green space had a stronger protective effect on mood disorder medications in census tracts with lower SES. Prescriptions related to cardiovascular health showed the opposite patterns as prescriptions pertaining to mental health. Gidlow *et al.* (2016) reported that cardiovascular prescribing volume was higher in residents of most deprived neighborhoods. In contrast, residents of the least deprived neighborhoods showed no associations between green space and the number of prescriptions. Chi *et al.* (2022) found green space had a stronger protective effect on cardiovascular medication in higher vs. lower SES tracts.

Two studies examined effect modification by urbanicity. Chi *et al.* (2022) reported tree stem density had stronger protective effects on mood disorder and cardiovascular medication sales in less densely populated census tracts. Aerts *et al.* (2022) found that green space cover had a stronger protective effect on sales of mood disorder medicines in urban than rural census tracts.

**Table 2.** Characteristics of studies on green space exposure and healthcare prescriptions (n = 15).

| *Authors Publication year; Study area* | *Sample size/unit of analysis; Population; Study design* | *Green space exposure* | *Health outcome data* | *Specific health outcome* | *Adjusted variables* | *Main findings* |
|---|---|---|---|---|---|---|
| (Aerts, Nemery, *et al.*, 2020) *Belgium* | Census units (n = 11,575) Adult (19-64 years) Ecological | Green space (forest patch, cover, cover) | Electronic health records (Belgian Social Security Agency) | Cardiovascular medication sales | Air pollution, socioeconomic deprivation | Living near green areas was associated with lower cardiovascular medication sales ($\beta = -0.71$, $p < 0.001$) |
| (Aerts, Dujardin, *et al.*, 2020) *Belgium* | Census units (n = 1,872) Children (6-18 years) Ecological | Grassland, garden, and forest cover | Electronic health records (Belgian Social Security Agency) | Asthma medication sales | Time, mean annual PM10 concentration, proportion of houses with basic or insufficient housing quality, administrative region | Living near grassland ($\beta$ = 0.15–0.17) and garden ($\beta$ = 0.13–0.17) was associated with poor children's respiratory health, leading to more prescribed asthma medication sales; Forest cover was protective against OAD medication sales ($\beta$ = –0.013, 95% CI: –0.025–0.000, p = 0.048) for 13-18 years old girls. |
| (Aerts *et al.*, 2022) *Belgium* | Census units (n =9,579) Adult (19-64 years) Ecological | Green space cover including woodland, low green, garden, grassland | Electronic health records (Belgian Social Security Agency) | Mood disorder medication sales | Socio-economic background, urban-rural differences, administrative region | Higher green space coverage was linked to reduced sales of mood disorder medication in the majority of cases studied. Specifically, a 10% increase in woodland, garden, and grass coverage was associated with a decrease in medication sales by 1.3%, 1.3%, and 2.1% for men and 1.8%, 0.7%, and 1.6% respectively for women. Additionally, for men, a 10% increase in low green coverage was linked to a 1.3% decrease in medication sales. |
| (Astell-Burt *et al.*, 2021) *Australia* | 55,339 people Adults (45 years or older) Cohort | Total green space cover; Tree canopy cover; Open grass cover | Electronic health records (Medicare Benefits Schedule (MBS) and Pharmaceutical Benefits Scheme (PBS) | Antidepressant prescribing, referral for talking therapy; Counts of antidepressants prescribed, counts of talking therapies referred | Age, sex, income, education, work status, relationship status | Green space was associated with higher antidepressant prescribing (IRR = 1.06, 95% CI = 1.04–1.08). Open grass was associated with increased odds (OR = 1.17, 95% CI = 1.13–1.20) and counts of antidepressant prescriptions (IRR = 1.05, 95% CI = 1.02–1.08) and lower |

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| | | | | | | talking therapy referrals (IRR = 0.93, 95%CI = 0.90–0.96). |
| (Chi *et al.*, 2022) *Belgium* | Census tracts (n = 604) Adults (18-64 years) Ecological | Tree height, crown diameter, crown volume, canopy cover, leaf area index | Electronic health records (Belgian social security agency) | Medication sales for mood disorders and cardiovascular disease | Percentage of immigrants from low- and middle-income countries; percentage of unemployed inhabitants; percentage of inhabitants with only primary education; immigrants from low-and mid-income countries | Higher crown volume was associated with a 34% decrease in mood disorder medication sales and a 21-25% decrease in cardiovascular medication sales. Conversely, higher stem density was associated with a 28-32% increase in mood disorder medication sales and a 20-24% increase in cardiovascular medication sales. |
| (Gidlow *et al.*, 2016) *England* | 1,600 people Adults Ecological | Natural environments, including public green spaces, gardens | Electronic health records (Health and Social Care Information Centre) | Cardiovascular prescribing volume; anti-depressant prescribing volume | Deprivation in education, skills, and training; deprivation in the living environment; urban-rural classification; ethnicity; proportion of the LSOA aged 20-64; proportion of the LSOA aged ≥65 years | A higher density of natural environment (public green spaces and gardens) was positively associated with cardiovascular prescribing. The association with antidepressant prescribing showed a non-significant trend towards lower rates in areas with higher natural environment density. |
| (Helbich *et al.*, 2018) *Netherlands* | 403 municipality Adults Ecological | Green space cover | Electronic health records (Netherlands Institute for Health Services Research.) | Antidepressant prescription rates | Elderly, unemployment, physical activity, housing value, distance to closest general practitioner, residential density, share of non-western residents | Green space showed an overall inverse and non-linear association with antidepressant prescription rates. |
| (Maantay and Maroko, 2015) *Scotland* | 690 data zones Adults (>16 years) Ecological | Vacant and derelict land density | Scotland Census, 2012 | Prescribed medication for anxiety, depression, or psychosis | Educational achievement, share of non-UK born residents, distance to basic services (medical office, post office, shopping centers, schools, gas stations) | Higher densities of vacant and derelict land were significantly associated ($\beta = 0.171$, $p = 0.000$) with higher rates of mental health prescriptions. |
| (Marselle *et al.*, 2020) *Germany* | 9,571 people Adults (18–79 years) Longitudinal | Public street trees; street tree abundance; species richness; spatial proximity of exposure; Street tree quantity | Questionnaires, interviews | Antidepressant prescriptions | Age, gender, marital status, employment status, net income, socioeconomic status, alcohol consumption, smoking behavior, BMI, season of the year | Greater street tree density within 100-m of the home was associated with lower antidepressant prescription rates (log OR = −0.09; SE = 0.05; 95% CI: –0.18 − 0.00; p = 0.057). |
| (McDougall *et al.*, 2021) *Scotland* | 2,128,997 people in 6,567 data zones Adults (50-64 years) & | Public green space coverage, total green space coverage | Electronic health records (Prescribing Information System for Scotland (PRISMS), Scotland | Antidepressant medication | Urbanicity, area-level gender differences, proportion of adults above 65 years old, proportion of income-deprived individuals, housing characteristics and | Neighborhoods with higher public green space coverage were associated with lower antidepressant medication prevalence among older adults. Total green space coverage was associated |

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| | Older people (>65 years old) Ecological | | | | living arrangements, percentage of individuals in each data zone living in overcrowded housing, crime rates | with higher antidepressant medication prevalence. |
| (Okokon *et al.*, 2021) *Finland* | 5,441 people Adults Cross-sectional | Arable land, pastures, forests, green urban areas, herbaceous vegetation associations, and open spaces with little or no vegetation were designated as green areas | Questionnaires | Medications, diagnoses, and treatment for hypertension | Age, sex, household income, mean area-level income, employment status, alcohol consumption, active smoking, passive smoking, BMI, physical exercise | No associations were observed between the environmental exposures and the use of antihypertensive medication or self-reported physician-diagnosed hypertension (OR (95% CI) = 0.99 (0.94-1.04). |
| (Roberts, Irvine and McVittie, 2021) *Scotland* | 4,467 data zones Older people (>65 years old) Ecological | Neighborhood green space; green space within 2-km buffer | Scottish Census data | Prescription drugs to treat depression, anxiety and psychosis (inverse log-transformed). | Proportion of black and minority, proportion of females, proportion of married, proportion of deprived, proportion with dependent children, proportion over 65, proportion of no religion, proportion of area garden | Higher levels of green space in the immediate neighborhood were associated with lower rates of mental health prescriptions for drugs used to treat depression, anxiety, and psychosis (estimate = 0.06, SE = 0.01, 95% CI = 0.04-0.08). However, green space with a 2km buffer was not associated with mental health prescriptions (estimate = 0.01, SE = 0.03, 95% CI = 0.04-0.06). |
| (Taylor *et al.*, 2015) *UK* | 33 boroughs Adults Ecological | Street trees | Greater London Authority | Antidepressant prescriptions | Socio-economic status, index of multiple deprivation, percentage of residents claiming job seekers' allowance, prevalence of smoking, borough mean age | Higher street tree density was associated with a slight reduction in anti-depressant medication prescriptions (1.18 fewer prescriptions per 1,000 people for each tree per km, 95% CI = -2.45, 0.00). |
| (Turunen *et al.*, 2023) *Finland* | 7,321 Adults (>25 years) Cross-sectional | Residential green space cover; frequency of green space visits; green views from the window | Questionnaires | Psychotropic medications; Anti-hypertensive medication use; Asthma medication use | Age, sex, marital status, education, employment status, annual household income, smoking, alcohol use, physical activity at work, using recreational properties during the warm season, area-level annual mean income, road traffic noise and NO2 from road traffic | Frequent visits to green spaces were associated with a reduced likelihood of using psychotropic medication, antihypertensive medication, and asthma medication. |

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| (White *et al.*, 2021) 18 Countries | 16,307 Adults Cross-sectional | Residential greenness; Frequency of visit to green space; Nature connectedness | Questionnaires | Anxiety medication use; Depression medication use | Sex, age, household income, employment status, education, long-term illness/disability, marital status, number of adults and children in household, dog and car ownership, weekly physical activity, season of data collection | A high frequency of green space visits was associated with reduced depression medication use (OR = 0.99, $p < 0.05$). Similarly, a negative association was observed between nature connectedness and the use of depression medication (OR = 0.83, $p < 0.05$). |

Notes: β, regression coefficient; OAD, obstructive airway disease; NDVI, normalized difference vegetation index; IRR, Incidence Rate Ratio; OR, Odds Ratio; CI, Confidence Interval; SE, Standard Error, BMI, Body Mass Index; LSOA, Lower Layer Super Output Area; PM10, Particulate Matter 10 (refers to fine particulate matter in the air with a diameter of 10 micrometers or less)

### *3.5.2. Healthcare expenditures*

Thirteen studies reported associations between green space exposure and healthcare expenditures (Table 3). Most (n = 11, 84%) reported beneficial associations of green space availability with lower total per capita healthcare expenditures (Rosenberger *et al.*, 2005; Becker *et al.*, 2019; Kabaya, 2020; Anwar, Madni and Yasin, 2021; Astell-Burt *et al.*, 2021; Becker and Browning, 2021; Van Den Eeden *et al.*, 2022). Further, urban forest proximity was associated with lower per capita healthcare expenditures (Kabaya, 2020). Two studies reported green space accessibility was associated with reduced per capita healthcare costs (Sato *et al.*, 2019; Wali *et al.*, 2022), of which one study indirectly associated it through greater bike-related moderate to vigorous physical activity (Wali *et al.*, 2022). More visits to green spaces were associated with reduced mental health care costs (Buckley and Chauvenet, 2022). In contrast, one Australian study reported that green space availability (tree canopy) was not associated with overall patient costs (Astell-Burt *et al.*, 2021). Open grass was associated with higher mean costs for talking therapy, and participants with more open grass tended to have higher total and mean per person costs for antidepressant prescriptions (Astell-Burt *et al.*, 2021). One more study reported greater densities of gardens were not protective in reducing healthcare costs (Gidlow *et al.*, 2016). Furthermore, nature views from home and poor quality of urban green space were not associated with healthcare costs (Kohn *et al.*, 2013; Zhang and Wu, 2022).

Two studies examined effect modification by SES. Gidlow *et al.* (2016) reported that the least deprived neighborhoods had higher cardiovascular-related medication costs, whereas more deprived neighborhoods showed no significant associations between green space and expenses. In contrast, Becker *et al.* (2019) found stronger protective effects of forest and shrub cover on older adults' healthcare expenditures in U.S. counties with lower median household incomes and educational achievement levels. Later, Becker & Browning (2021) reported similar effects of greenness on older adults' healthcare expenditures across most levels of urbanicity in U.S. counties.

**Table 3.** Characteristics of studies on green space exposure and healthcare expenditures (n = 13).

| *Author (s), Publication Year, Study area* | *Sample Size/Unit Study Population Study design* | *Exposure variables* | *Outcome assessment source* | *Outcome Name* | *Adjusted variables* | *Main findings* |
|---|---|---|---|---|---|---|
| (Anwar, Madni and Yasin, 2021) *87 countries* | Panel data (n = 87 countries) NR Longitudinal | Forest cover | World Development Indicators (WDI) | Health expenditures | Per capita income, trade, and industrial value-added | Forest area was inversely associated with healthcare expenditures among low-income and partner countries of OBOR, while positively associated among upper-middle-income countries. |
| (Astell-Burt *et al.*, 2021) *Australia* | 55,339 Adults (45 years or older) Cohort | Total green space cover; tree canopy cover; open grass cover | Electronic health records (Medicare Benefits Schedule, Pharmaceutical Benefits Scheme) | Total costs of antidepressant prescriptions, mean costs of antidepressant prescriptions and talking therapy referrals per participant | Age, sex, income, education, work status, relationship status | Tree canopy coverage was associated with increased patient contributions to overall costs. However, a 10% increase in open grass was associated with lower total costs, means ratio (MR), = 0.91, 95% CI = 0.85–0.98) and total individual contribution (MR = 0.90, 95% CI = 0.83–0.97). |
| (Becker and Browning, 2021) *USA* | 3,091 counties Adults Ecological | Greenness (NDVI) | Electronic health records (Center for Medicare and Medicaid Services) | Per capita Medicare expenditure | Age, sex, race, number of doctors, hospitals, and hospital beds, poverty rate, Medicaid eligibility rate, urbanicity, education-income index, Medicare price index | Greenness is negatively associated ($\beta = -632.0$ $p = 0.002$) with healthcare spending. |
| (Becker *et al.*, 2019) *USA* | 3,103 counties Older people (>65 years) Ecological | Green land cover (Forest, Shrub, Grass, Urban vegetation) | Electronic health records (Center for Medicare and Medicaid Services) | Medicare fee-for-service expenditures | Gender, race, area, age, log population, education-income index, user concentrations, doctors, hospitals, hospital beds, particulates, inactivity | Forest ($\beta = -0.11$, $p = < .001$) and shrub ($\beta = -0.12$, $p = < .001$) cover were inversely associated with median Medicare fee-for-service spending. |
| (Buckley and Chauvenet, 2022) *Australia* | 19,764 Adults Cross-sectional | Park visits, green space visits | Questionnaires | Mental health care costs | Age, BMI, gender, health service use, residential area (urban/rural), education, employment, exercise, income, number of children | Public visits to protected areas in Australia increased economic productivity by 1.8% and reduced healthcare expenditure by 0.6%. |
| (Gidlow *et al.*, 2016) *England* | 1,600 Adults Ecological | Natural environments (public green spaces, gardens) | Electronic health records (Health and Social Care Information Centre) | Cardiovascular prescribing cost; Anti-depressant prescribing cost | Deprivation in education, skills, and training, deprivation in the living environment; urban-rural classification; ethnicity; the | Higher density of natural environment (public green spaces, gardens) showed a non-significant |

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| | | | | | proportion of the LSOA population aged 20-64; the proportion of the LSOA population aged ≥65 years | association with cardiovascular and anti-depressant prescribing costs. |
| (Kabaya, 2020) *Japan* | 47 prefectures Adults Ecological | Overall forest cover, evergreen forest cover, deciduous forest cover, mixed forest cover, forest proximity score, forest diversity score | National Health Insurance annual reports, Japan | Per capita health expenditure | Income, elderly, population density, number of hospital beds per 1000 population | Mixed forest coverage and proximity to urban forests were found to have significant inverse long-term effects on per capita health expenditure. In contrast, no empirical evidence of short-term health impacts was observed. |
| (Kohn *et al.*, 2013) *USA* | 6,631 ICU patients Cohort | Windows or natural views | Electronic health records | Hospitalization costs | Age, sex, race, and source of intensive care unit (ICU) admission | Windows or natural views in ICU rooms do not reduce medical and surgical ICU patient costs. |
| (Rosenberger *et al.*, 2005) *USA* | 55 county Older people (>65 years old) Ecological | Municipal land, public land, recreation water, recreation facilities, Parks & Recreation Department | Electronic health records (West Virginia's state agencies, USA) | Health care expenditures | Population over the age of 65 years, education level, median age, per capita income in the equation | Recreation opportunities were found to have a negative association with health care expenditures indirectly through their direct effect on physical inactivity. |
| (Sato *et al.*, 2019) *USA* | 3,134 counties Older people (>65 years old) Ecological | Access to parks, Recreational facilities | Electronic health record (Dartmouth Atlas of Health Care) | Health care costs | Percentage of adults aged 65 and over reporting leisure-time physical activity | Improved access to parks and recreational facilities decreased per-person healthcare costs for older adults by $0.18 in 2013 and $0.16 in 2014. |
| (Van Den Eeden *et al.*, 2022) *USA* | 5,189,303 Adults (<20-80+ years) Longitudinal | Greenness (NDVI) in 250-m, 500-m, 1000-m buffers around the home | Electronic health records (Internal Cost Management Information System, Kaiser Permanente Northern California) | Total costs, hospitalization costs, outpatient costs, emergency room costs, pharmacy costs | Small area household income, education level, housing density and population density, Neighborhood Deprivation Index, air quality (PM2.5) around the residence | Higher levels of residential green cover were associated with lower direct healthcare costs, with a relative rate of total cost of 0.92 (95% CI 0.90–0.93) for the highest compared to the lowest decile of greenness within a 500-m buffer. |
| (Wali *et al.*, 2022) *USA* | 476 Adults (18-75 years) Cross-sectional | Community gardens | Electronic health records (Internal Cost Management Information System, Kaiser Permanente Northern California) | Health care costs | Residential choices (closeness to bus stop, closeness to shops & services), preferences/attitudes (pro-bike, walking easier, use car sharing service, sociodemographic factors (income, gender, age, | Community gardens were negatively associated with health care costs through greater bike-related MVPA. |

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| | | | | | education, race, marital status, number of children) | |
| (Zhang and Wu, 2022) *China* | 1,000 Adults (>18 years) Cross-sectional | Amount of urban green space (UGS), demand for UGS activity, supply of UGS activity, total UGS; amount of nearby UGS (perceived); quality of UGS | Questionnaires | Total health expenditures, health insurance expenditures, medical product expenditures, health-related book and course expenditures | Demographic and socioeconomic factors (Gender, age, marital status, residence house, occupation, monthly income, housing size, number of children, academic qualifications) | A lower number of urban green spaces was associated with a higher likelihood of low total health expenditures, health insurance expenditures, medical product expenditures, and health-related book and course expenditures. Poor perceived quality of the most frequently visited UGS was associated with higher total health expenditures, health insurance expenditures, and a greater number of medical visits. Moreover, worse UGS quality for ball and dance activities and poor viewing quality were linked to higher total health expenditures in the 2000-5000 Chinese Yuan range. |

Notes: β, regression coefficient; OAD, Obstructive airway disease; NDVI, Normalized difference vegetation index; OBOR, one belt one road; MVPA, Moderate-to-Vigorous Physical Activity

### 3.6. Risk of bias assessments

The details of the risk of bias assessment for individual studies are illustrated in Table S8. Across both outcomes, one article (4%) had a Tier 1 overall risk of bias, while the remaining 25 articles (96%) had Tier 2 risks of bias (Table 4). No articles had a Tier 3 risk of bias.

The risk of bias varied dramatically across individual domains (Table 4). Bias in exposure classification reported 19% 'Probably low,' 77% 'Probably high' and 4% 'Definitely high' risk of bias. More than half (76%, n = 16) showed a 'Definitely low' risk of bias for outcome measurements. Meanwhile, 38% (n = 10) of the articles reported a 'Probably high' risk due to confounding. Higher shares of 'Definitely low' risk of bias were found for selection bias (85%), attrition/exclusion bias (96%), selective reporting bias (100%), conflict of interest (96%) and other bias (100%), respectively.

For prescriptions, all studies were categorized as Tier 2 risk of bias. The primary contributors to these studies' risks of bias were bias in exposure classification, outcome classification and confounding. These studies largely adjusted for Tier 1 individual-level confounding variables such as age, sex, education, income, employment, and SES.

For expenditures, one study had a Tier 1 risk of bias (Van Den Eeden *et al.*, 2022), and the remaining eleven had a Tier 2 risk of bias. These studies' risks of bias were mainly attributed to bias in exposure classification, confounding, and outcome classification.

**Table 4.** Risk of bias rating for included studies determined by OHAT tool.

| **Author (s), Year** | Detection bias for exposure | Detection bias for outcome | Confounding bias | Selection bias | Attrition/exclusion bias | Selective reporting bias | Conflict of interest bias | Other bias | **Summary tiered classification** |
|---|---|---|---|---|---|---|---|---|---|
| (Aerts, Nemery, *et al.*, 2020) | - | ++ | - | ++ | ++ | ++ | ++ | ++ | T2 |
| (Aerts, Dujardin, *et al.*, 2020) | - | ++ | - | ++ | ++ | ++ | ++ | ++ | T2 |
| (Aerts *et al.*, 2022) | - | ++ | - | ++ | ++ | ++ | ++ | ++ | T2 |
| (Anwar, Madni and Yasin, 2021) | - | ++ | - | - | ++ | ++ | ++ | ++ | T2 |
| (Astell-Burt *et al.*, 2021) | - | ++ | ++ | ++ | ++ | ++ | + | ++ | T2 |
| (Becker and Browning, 2021) | - | ++ | ++ | ++ | ++ | ++ | ++ | ++ | T2 |
| (Becker *et al.*, 2019) | - | ++ | + | + | ++ | ++ | ++ | ++ | T2 |
| (Buckley and Chauvenet, 2022) | -- | -- | ++ | ++ | ++ | ++ | ++ | ++ | T2 |
| (Chi *et al.*, 2022) | - | ++ | - | ++ | + | ++ | ++ | ++ | T2 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| (Gidlow *et al.*, 2016) | - | ++ | + | ++ | ++ | ++ | ++ | ++ | T2 |
| (Helbich *et al.*, 2018) | - | ++ | - | ++ | ++ | ++ | ++ | ++ | T2 |
| (Kabaya, 2020) | - | ++ | - | ++ | ++ | ++ | ++ | ++ | T2 |
| (Kohn *et al.*, 2013) | - | ++ | + | + | ++ | ++ | ++ | ++ | T2 |
| (Maantay and Maroko, 2015) | - | + | - | ++ | ++ | ++ | ++ | ++ | T2 |
| (Marselle *et al.*, 2020) | - | + | ++ | ++ | ++ | ++ | ++ | ++ | T2 |
| (McDougall *et al.*, 2021) | - | + | ++ | ++ | ++ | ++ | ++ | ++ | T2 |
| (Okokon *et al.*, 2021) | + | -- | ++ | ++ | ++ | ++ | ++ | ++ | T2 |
| (Roberts, Irvine and McVittie, 2021) | - | + | + | ++ | ++ | ++ | ++ | ++ | T2 |
| (Rosenberger *et al.*, 2005) | - | ++ | + | + | ++ | ++ | ++ | ++ | T2 |
| (Sato *et al.*, 2019) | - | ++ | - | ++ | ++ | ++ | ++ | ++ | T2 |
| (Taylor *et al.*, 2015) | - | ++ | + | ++ | ++ | ++ | ++ | ++ | T2 |
| (Turunen *et al.*, 2023) | + | -- | ++ | ++ | ++ | ++ | ++ | ++ | T2 |
| (Van Den Eeden *et al.*, 2022) | + | + | ++ | ++ | ++ | ++ | ++ | ++ | T1 |
| (Wali *et al.*, 2022) | - | ++ | - | ++ | ++ | ++ | ++ | ++ | T2 |
| (White *et al.*, 2021) | + | -- | ++ | ++ | ++ | ++ | ++ | ++ | T2 |
| (Zhang and Wu, 2022) | + | -- | ++ | ++ | ++ | ++ | ++ | ++ | T2 |

| **Level of Risk of Bias** | | | | | | | |
|---|---|---|---|---|---|---|---|
| ++ | Definitely low | + | Probably low | - | Probably high | -- | Definitely high |

T1, Tier 1; T2, Tier 2

### 3.7. Overall quality of evidence

Our assessments, guided by the criteria for evaluating evidence quality outlined in Table S9, yielded the following conclusions. For healthcare prescriptions, a downgrade of one level was supported for 'risk of bias' because most studies in the review reported a Tier 2 risk of bias. Similarly, a downgrade of one level was applied to healthcare expenditures for 'risk of bias' because most studies had a Tier 2 risk of bias. Consequently, the quality of evidence for both health outcomes (expenditures and prescriptions) was low (Table S9).

### 3.8. Strength of evidence

Following the established criteria for evaluating the strength of evidence outlined in Table S5, we conducted the following assessments, summarized in Table S11. For both healthcare outcomes, the evidence for greenspace being associated with lower expenditures or prescription medications was classified as "limited."

## 4. Discussion

### 4.1. Summary of main findings

This is the first systematic review to explore whether green space exposure is associated with reduced healthcare expenditures and pharmaceutical prescriptions. We found 26 studies on this topic that were published through May 2023. These studies reported 242 associations between green space and healthcare outcomes. Thirty-four percent (n=83) of these associations were statistically significant and in the protective direction.

The overall low quality of evidence we observed reflects concerns about risks of bias in the extant literature, impacting the robustness of the review's conclusions. Stemming from variations in study results and these risks of bias, the evidence for green space being beneficially associated with lower prescription rates and healthcare expenditures was limited.

Still, the potential for green space being beneficially associated with these outcomes is supported by other reviews. An umbrella review of 40 systematic reviews and meta-analyses found that green space exposure reduced the risk of all-cause and stroke-specific mortality, cardiovascular disease, cardiometabolic factors, poor mental health, low birth weight, physical inactivity, and poor sleep quality (Yang *et al.*, 2021). A 2020 systematic review of four journal articles, one book chapter, and five reports identified support for natural environments in cities being linked to statistically significant and economically meaningful health improvements (Chen, 2020). Meanwhile, a narrative review of studies found considerable indirect support for similar relationships (Wolf and Robbins, 2015).

### 4.2. Explanation for main findings

#### 4.2.1. Previously discussed mechanisms

Green space is associated with dozens of pathways that could improve health status (Kuo, 2015; Twohig-Bennett and Jones, 2018). In addition to supporting physical activity, natural environments may improve sleep (Shin *et al.*, 2020) and other health-promoting behaviors (Hartig *et al.*, 2014; Markevych *et al.*, 2017). Individuals living in greener settings may experience cognitive and emotional restoration, which reduces stress and attentional fatigue (Ulrich, 1983; Kaplan, 1995). Pro-social interactions and supportive exchanges between individuals can be facilitated by natural environments, supporting relational and collective resources that can improve health status (Hartig, 2021; Astell-Burt *et al.*, 2022). Greener environments can also mitigate the harmful effects of air pollution (Mueller *et al.*, 2020), noise (Dzhambov *et al.*, 2018), and heat (Doick, Peace and Hutchings, 2014) on health and promote exposure to commensurate microbiota (Mills *et al.*, 2020).

The mechanisms underlying the potential for green space exposure to impact healthcare expenditures or prescription rates are largely unexplored, but some have already been discussed. One theory is that green space exposure improves health status, which translates into reduced utilization (including prescription medications) and downstream effects on expenditures (Van Den Eeden *et al.*, 2022). The authors of this theory tested it by adding mediators (i.e., comorbidities, smoking, and body weight) to their models of green space and per-person annual healthcare costs with a cohort of over five million Kaiser Permanente Northern California members. They found that these mediators attenuated the strength of the associations of green space with costs, supporting this theory.

Other studies support green space improving health status and, in turn, reducing healthcare expenditures. Three studies reported that increased leisure-time physical activity negatively associated green space access with healthcare expenditures (Rosenberger *et al.*, 2005; Sato *et al.*, 2019; Wali *et al.*, 2022). Regular physical activity can improve physical health and reduce the risk of chronic diseases, including obesity and diabetes (Durstine *et al.*, 2013), which could translate to lower healthcare expenditures.

#### 4.2.2. Additional mechanisms and factors

A number of other explanations for the impact of green space exposure on healthcare outcomes may exist. Our exploration of other mechanisms was driven by the contrasting findings we observed and the disparate modifying effects of SES and urbanicity. For instance, some of our reviewed articles reported that green space availability was associated with higher antidepressant prescription rates, cardiovascular disease medication rates, and costs for referrals for talking therapy in some contexts (Astell-Burt *et al.*, 2021; Chi *et al.*, 2022). While these discrepancies could stem from myriad differences - from green space and outcome measurements to the study context (i.e., urbanicity, climate, and planning policies) and population (i.e., sociodemographics and health status) - we also observed stark contrasts in effects among the six studies that conducted stratified analyses by SES and urbanicity.

We posit that these contrasting findings on green space and healthcare outcomes might relate to social drivers of health. This recommended replacement for “social determinants of health” encompasses the social and economic factors affecting human health (Lumpkin *et al.*, 2021). Such drivers may modify the associations of green space with human health and, ultimately, healthcare outcomes. For instance, lower-income residents may benefit more strongly from residential greenery than higher-income residents due to suppressed baselines, neighborhood dependencies, and a lack of other health-promoting spaces (Rigolon *et al.*, 2021). However, the strengthened health benefits of green space among lower-income residents may not translate into decreased healthcare expenditures. Lower-income residents tend to engage less in preventative health services, such as screenings and annual check-ups, due in part to being uninsured or underinsured coupled with limited access to primary care providers and elect instead to engage when sick with a disease or illness (Frees, Gao and Rosenberg, 2011; Yu, Alavinia and Alter, 2020; Loef *et al.*, 2021). Less preventative health maintenance may lead to higher healthcare costs downstream, such as hospitalizations (Galvani *et al.*, 2020).

Urbanicity and rurality further complicate the effects of social drivers of health on green space and healthcare outcomes. There is an inherent, inverse relationship between urbanicity (i.e., impervious surfaces like roads, buildings, and parking) and greenery (Li *et al.*, 2023b; Yuan and Bauer, 2007). While green space in rural areas has been associated with better health status (Browning *et al.*, 2022b), rural areas also have barriers to engaging with healthcare systems. Access to healthcare in rural areas is often limited by insurance coverage, lack of special care providers, cost concerns, and long waits for outpatient visits (Huttlinger, Schaller-Ayers and Lawson, 2004; Fasolino and Koci, 2022). Psychological barriers can exist as well. For instance, individuals who value self-sufficiency may seek homes in rural areas with high levels of green space but distance themselves from institutions and modern life, including formal healthcare (Ford, 2019). Stigmas, spiritual beliefs, and distrust can also prevent more rural residents from receiving proper treatment and participating in health promotion programs (Jesse and Reed, 2004; Behringer and Krishnan, 2011; Witt and Hardin-Fanning, 2021).

Rural areas have other strong social drivers of health alongside their high green space levels. Food deserts and food swamps can be commonplace, with affordable access to processed nutrient-poor products dominating over healthy and fresh food (Mulangu and Clark, 2012; Karpyn *et al.*, 2019; Phillips and Rodriguez, 2020). Rural areas tend to have higher disability rates in some parts of the world (Altman and Bernstein, 2008), negatively impacting health status and the ability to visit outdoor green spaces even if available (Corazon *et al.*, 2019). Rural areas can have fewer employment opportunities than urban areas, influencing socioeconomic sequelae of health status and utilization, with available options including industries with more environmental and occupational hazards (Hansen and Donohoe, 2003; Hendryx, 2015; Shriver and Bodenhamer, 2018). Similarly, rural areas can have fewer opportunities for digital resources, advanced education, and community support for educational achievements, constraining health literacy and healthy lifestyle behaviors (Raghupathi and Raghupathi, 2020; Statti and Torres, 2020). Additionally, rural areas with industrial agricultural fields or commercial plant nurseries can expose residents and employees to high levels of pesticides and herbicides, risk factors for several diseases and illnesses (Schreinemachers, 2003; de Graaf *et al.*, 2022). The implication of more rural areas having poorer health is that residential green space is unlikely to always translate to lower healthcare expenditures. Tests of rurality as a confounder or effect modifier were present in four reviewed studies but showed inconsistent findings, warranting further research into its role in green space and healthcare outcome associations (Becker *et al.*, 2019; Becker and Browning, 2021; Aerts *et al.*, 2022; Chi *et al.*, 2022).

Additionally, substance abuse can confound relationships between green space, health status, and healthcare outcomes. Substance abuse encompasses the use of illegal drugs, misuse of prescription medications, excessive alcohol use, and potential consequences of substance use disorder (Rowe and Liddle, 2003). For instance, one study from the U.S. found positive associations between green space and rates of opioid-related mortality at the county-level (Becker *et al.*, 2022) despite other evidence suggesting green space should be associated with less opioid use disorder as a consequence of better pain management, mental and physical health, ability to delay rewards, social connectedness, and substance cravings (Berry *et al.*, 2021). These unexpected findings could be explained by dense forests co-occurring in areas with high rates of opioid prescriptions due to a confluence of factors, including high rates of poverty and unemployment, lack of comprehensive health insurance coverage, and high rates of employment in manual labor industries, such as lumber and mining (Moody, Satterwhite and Bickel, 2017; Becker *et al.*, 2022).

#### 4.2.3. A conceptual framework of green space and healthcare outcomes

A general limitation of the extant literature on green space and healthcare outcomes is the lack of a coherent, dedicated conceptual framework integrated within the broader research on nature and health (Hartig *et al.*, 2014; Markevych *et al.*, 2017; Marselle *et al.*, 2021; Astell-Burt *et al.*, 2022; White *et al.*, 2023). Such a framework is necessary to guide future research and support practical applications. As a starting point for developing such a framework, we recognize that expenditures and prescriptions are downstream of health status but also influenced by barriers to accessing healthcare services and social drivers of health (i.e., rurality, SES, race and ethnicity, sex, age, spoken language, and disability).

Figure 7 fuses the results of this review with these upstream factors of healthcare utilization to present a conceptual framework that clarifies how residential green space may impact the use of and spending on formal healthcare. As previously discussed, residential green space can lead to health benefits via multiple pathways, organized in domains defined by their adaptive relevance: supported sleep, exercise, positive social relationships, and healthy commensurate microbiota exposure; adaptive reactions and restoration of depleted capacities such as attentional and emotional resources; and harm mitigation including pollution, heat, and noise. However, green space can also present allergens (i.e., pollen) and increase the risk of vector-borne diseases, such as Lyme disease from ticks (Hough, 2014; Marselle *et al.*, 2021; Hansford *et al.*, 2022) and in rare occurrences, dangerous wildlife encounters (Soga and Gaston, 2022). Increasing physical activity in green spaces and other natural environments also has some risks of accidental injury (Li *et al.*, 2023b; Nilsson, Sangster and Konijnendijk, 2011; Jennings, Browning and Rigolon, 2019; Ball and Ball-King, 2021; Marselle *et al.*, 2021) and can lead to overuse and chronic injuries (Viljoen *et al.*, 2021).

These conflicting forces of green space exposure on health status will likely manifest in differing effects on downstream healthcare outcomes. Green space is likely to be linked with better health status and reduced healthcare expenditures in areas with high levels of access and utilization of healthcare systems. However, greenspace may reveal inconsistent or harmful associations with healthcare expenditures in areas with low levels of access or utilization of healthcare systems. An example of such a scenario is residents living in remote rural areas with high green space levels and strong barriers to accessing health care.

Sufficient attention to these moderators is critical to understanding better the possible outcomes suggested by this conceptual framework. A better understanding would inform public health and economic policy around nature-based interventions. Maintaining green space in neighborhoods may not drive down healthcare spending if barriers to healthcare access continue to persist in these communities.

### 4.3. Limitations of existing literature

Several exposure-related factors limit the prevailing literature's ability to robustly examine green space and healthcare outcomes. Most studies assessed green space exposure at a single time, often shortly before or at the time of the outcome, potentially missing long-term effects. Temporality helps establish the direction of causality and provides insights into whether exposure to green space precedes or follows changes in healthcare costs (Rothman and Greenland, 2005). However, the effects of green space are likely to accumulate and grow across the lifecourse (Astell-Burt, Mitchell and Hartig, 2014; Wolf *et al.*, 2015; Pearce *et al.*, 2018; Browning *et al.*, 2022), such that estimates should be weighted by length of residency at each address to calculate cumulative exposures accurately. Next, many studies reported green space availability at the census unit or county level, representing broad geographic regions rather than individual-level exposures. These ecological fallacies overlook variations in how individuals within large geographies experience and interact with green space in their immediate environments. The studies that measured green space availability within buffers around points of interest, such as homes, were constrained mainly to straight-line measures that might not effectively capture walking or commuting routes (Labib, Lindley and Huck, 2020; Ye *et al.*, 2022). Most studies calculated only the quantity of green space rather than assessing its quality or types (Nguyen *et al.*, 2021), including structural and functional aspects (Sanders *et al.*, 2015). The effectiveness of green space in influencing health outcomes may be linked to its usability (Ye *et al.*, 2022), yet the vast majority of the studies reviewed did not account for the quality of green space exposure. Only three studies incorporated surveys of perceived green space usage. Additionally, few studies considered visits to green space or the visibility of greenery, which are incredibly relevant for urban greening policy and standards, such as the "3-30-300" rule (Konijnendijk, 2022; Browning *et al.*, 2024).

Future research can improve the existing literature in several ways. To rule out residual confounding and moderating effects, studies can carefully examine multiple measures of SES (i.e., individual- and area-level income, educational achievement, and home value) and urbanicity (i.e., population density, residential density) (Browning *et al.*, 2022b; Browning and Rigolon, 2018; Rigolon *et al.*, 2021). Additional confounders and potential mediators/moderators, such as car and dog ownership, may exist and should be examined (White *et al.*, 2018; Rigolon *et al.*, 2021). Researchers can prioritize individual-level, quasi-experimental and longitudinal designs over observational and ecological designs in response to the need for implementation science in this field of research (Marvier *et al.*, 2023). Evaluation and thorough reporting of outcome variables may be necessary, with electronic medical records (EMRs) being valuable sources of objective healthcare expenditure data. Last, research can incorporate diverse green space exposure metrics, including objective, subjective, and expert assessments (Rhew *et al.*, 2011; Knobel, Dadvand and Maneja-Zaragoza, 2019; Knobel *et al.*, 2020) of accessibility, availability, and visibility (Labib, Lindley and Huck, 2020) within network buffers or GPS-trajectories of participants.

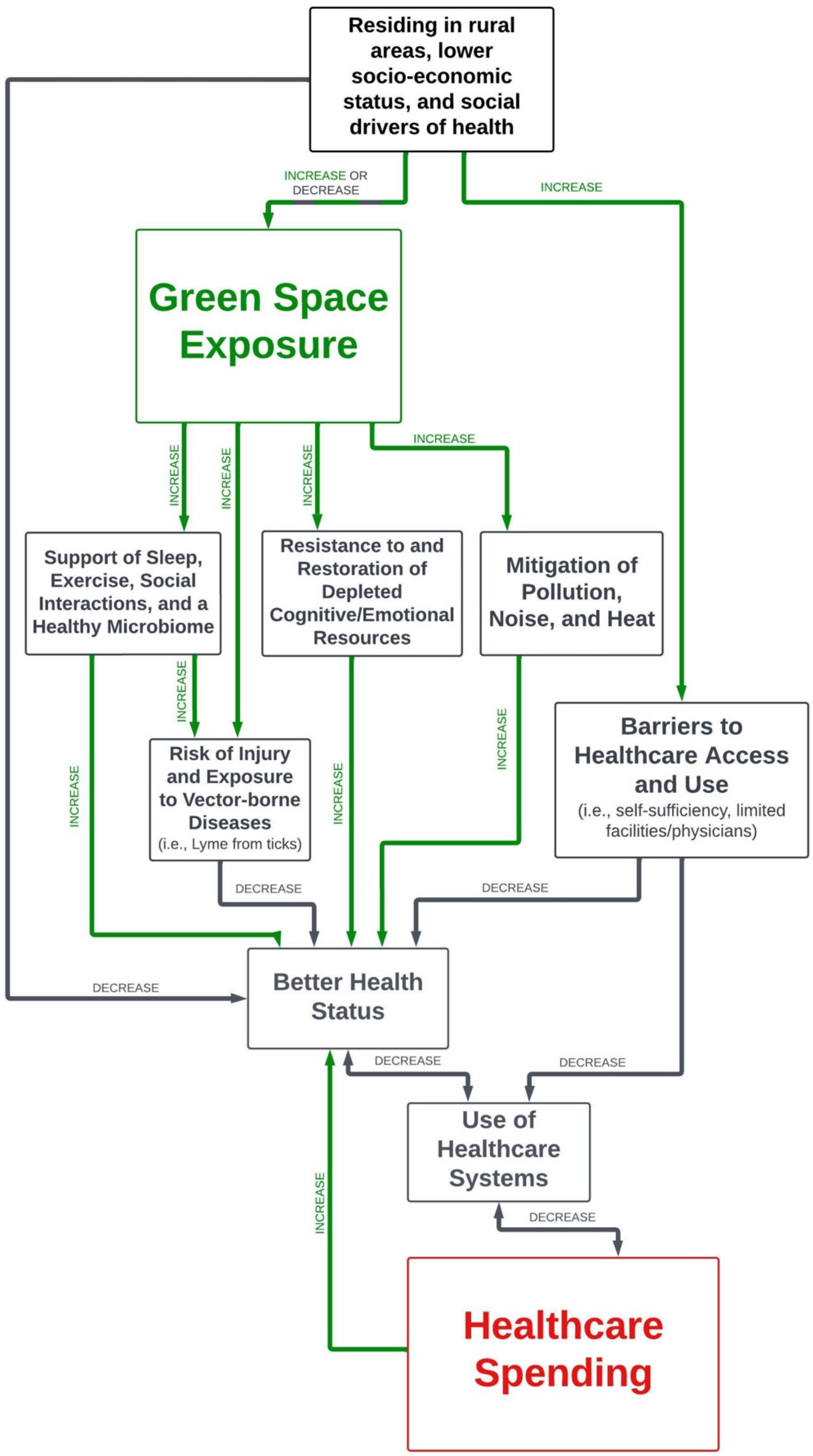


**Figure 7.** Conceptual framework explaining the complex pathways between residential green space and using or spending on healthcare systems.

### 4.4. Strengths and limitations of the review

This review was the inaugural effort to systematically and critically consolidate evidence for linkages between green space exposure and healthcare prescriptions and expenditures. Prior reviews on one or more of these topics employed narrative approaches or did not consider the risk of bias and quality of evidence (Wolf *et al.*, 2015; Chen, 2020; Busk *et al.*, 2022). However, the current review also has its limitations. The lack of age-specific stratification within the reviewed literature restricted our ability to acknowledge how healthcare expenses varied across the lifespan (Lassman *et al.*, 2014). Restricting our search to English keywords limited our ability to capture research conducted in non-English-speaking countries. This could affect the generalizability of our findings and overlook important cultural or geographical variations in the relationship between green space, health, and healthcare costs. Our review summarized information mainly from high-income countries rather than LMICs, which tend to experience substantial healthcare burdens and inequities in access to green space (Rigolon *et al.*, 2018). Tailoring research to local contexts, considering factors like climate, culture, level of development, healthcare system, and available infrastructures, among other important determinants, would inform to what extent nature-based solutions can potentially reduce healthcare outcomes globally.

## 5. Conclusion

This systematic review of 26 studies explored the connections between green space exposure and healthcare prescriptions and expenditures. The majority found beneficial associations between green space and expenditures or pharmaceutical prescriptions. Most studies were rated as Tier 2 risks of bias. The GRADE assessment concluded a limited strength of evidence of green space being linked with reduced healthcare prescriptions and expenditures. Based on these results and other literature, we presented a conceptual framework that explains the complex mechanisms between green space and healthcare outcomes. This differs from existing green space and health models by including upstream factors related to healthcare access (e.g., rurality, SES), which may flip the direction of associations between residential green space and healthcare expenditures. Additional research with lower risks of bias is necessary to validate this framework and better understand the potential for green space to reduce spending on healthcare.

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## Author contributions

M.H.E.M.B., M.P., & M.B. conceptualized the study, created the methodology, wrote the original draft, and created visualizations. M.P. & M.B. conducted data curation and analysis. All other authors contributed to reviewing and editing.

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