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Neighbourhood environments and cognitive health in the longitudinal Personality and Total Health (PATH) through life study: A 12-year follow-up of older Australians

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ABSTRACT

Background: Urban neighbourhood environments may impact older adults' cognitive health. However, longitudinal studies examining key environmental correlates of cognitive health are lacking. We estimated cross-sectional and longitudinal associations of neighbourhood built and natural environments and ambient air pollution with multiple cognitive health outcomes in Australian urban dwellers aged 60+ years.

Methods: The study included 1160 participants of the PATH Through Life study (60+ cohort) who were followed up for 12 years (four assessments; 2001/02 to 2013/15) and with data on socio-demographics, health, cognitive functions and diagnoses, and full residential address. Neighbourhood environmental features encompassed population and street-intersection densities, non-commercial land use mix, transit points, presence of blue space, percentages of commercial land, parkland and tree cover, and annual average $PM_{2.5}$ and NO_2 concentrations. All exposures except for tree cover were assessed at two time points. Generalised additive mixed models estimated associations of person-level average, and within-person changes in, exposures with cognitive functions. Multi-state hidden Markov models estimated the associations of neighbourhood attributes with transitions to/from mild cognitive impairment (MCI).

Results: Dense, destination-rich neighbourhoods were associated with a lower likelihood of transition to MCI and reversal to no MCI. Positive cross-sectional and longitudinal associations of non-commercial land use mix, street

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intersection density and percentage of commercial land were observed especially with global cognition and processing speed. While access to parkland and blue spaces were associated with a lower risk of transition to MCI, the findings related to cognitive functions were mixed and supportive of an effect of parkland on verbal memory only. Higher levels of $PM_{2.5}$ and NO_2 were consistently associated with steeper declines and/or decreases in cognitive functions and worse cognitive states across time.

Conclusion: To support cognitive health in ageing populations, neighbourhoods need to provide an optimal mix of environmental complexity, destinations and access to the natural environment and, at the same time, minimise ambient air pollution.

1. Introduction

Global increasing trends in population ageing (United Nations, 2017) and urbanisation (World Bank, 2020) call for the creation of cities that support healthy and independent living in the community in late life. This includes the provision of neighbourhood environments that promote cognitive health (i.e., the ability to clearly think, learn and remember) (National Institute on Aging, 2020), which is often compromised in late adulthood but is essential for independent living and successful ageing (World Health Organization, 2017). Cognitive health encompasses the absence of a clinical diagnosis of dementia or mild cognitive impairment (MCI), which are associated with significant disability and medical costs (Alzheimer's Association, 2021), as well as an individual's "optimal cognitive function", such as slower trajectories of age-related cognitive decline than the norm.

In the last decade, the number of studies on neighbourhood environmental correlates of cognitive health in older adults has increased exponentially (Chen et al., 2022; Delgado-Saborit et al., 2021). Despite this, several significant issues remain. Firstly, while they collectively examined all main categories of environmental features – namely, the built environment (e.g., street networks, dwellings and services), natural environment (e.g., green and blue spaces) and urbanisation by-products (e.g., air pollution and noise) – only a few considered all three categories, which is important given that these are causally interrelated (see Fig. 1) (Cerin, 2019; Cerin et al., 2021). Specifically, from a theoretical standpoint, urbanisation, operationalised as population or dwelling density, may have beneficial effects on cognitive health by providing easy access to services, transport infrastructure and social networks (Cerin et al., 2021; Chen et al., 2022) that promote a physically, socially and cognitively active lifestyle (Besser et al., 2017; Cerin et al., 2021; Clarke et al., 2012). Yet, densely populated neighbourhoods are often accompanied by poorer access to green spaces and higher levels of environmental stressors, such as traffic-related noise and air pollution (Cerin, 2019; Moore et al., 2003), which may harm cognitive health by deterring engagement in outdoor activities and increasing systemic inflammation and oxidative stress, which are risk factors for cardiovascular diseases (Brook, 2008), Alzheimer pathology (Cherbuin et al., 2022) and MCI (Cherbuin et al., 2019).

With respect to the natural environment, living in neighbourhoods with a greater amount of greenery has been linked to a lower risk of all-cause dementia, MCI and Alzheimer's disease (Aitken et al., 2021; Godina et al., 2023; Hu et al., 2023; Yuchi et al., 2020). Green spaces have also been associated with a slower rate of cognitive decline (Besser et al., 2021b; Cherrie et al., 2018; de Keijzer et al., 2018; Zhu et al., 2019). Interestingly, the evidence from longitudinal studies has been more consistent than that from cross-sectional studies, possibly in part due to lack of adjustment for residential self-selection – i.e., choosing to live in a neighbourhood that suits one's lifestyle (Cerin et al., 2021) – given that there is evidence that residential self-selection bias may strengthen (Besser et al., 2021a) or attenuate environment-behaviour-health associations (James et al., 2015). Green spaces as well as blue spaces (i.e., water bodies such as rivers, lakes and oceans) are deemed to benefit cognitive health by promoting engagement in leisure-time physical and social activities (Maas et al., 2009; Van Cauwenberg et al., 2018), reducing stress (de Keijzer et al., 2020) and pollution (Hirabayashi & Nowak, 2016), and facilitating the restoration of voluntary attention, which may be depleted by the complexity of daily tasks required in an urban environment (de Keijzer et al., 2020). However, the evidence on the effects of blue spaces on cognitive health is sparse and contradictory (Cerin et al., 2022; Klompmaker et al., 2022;

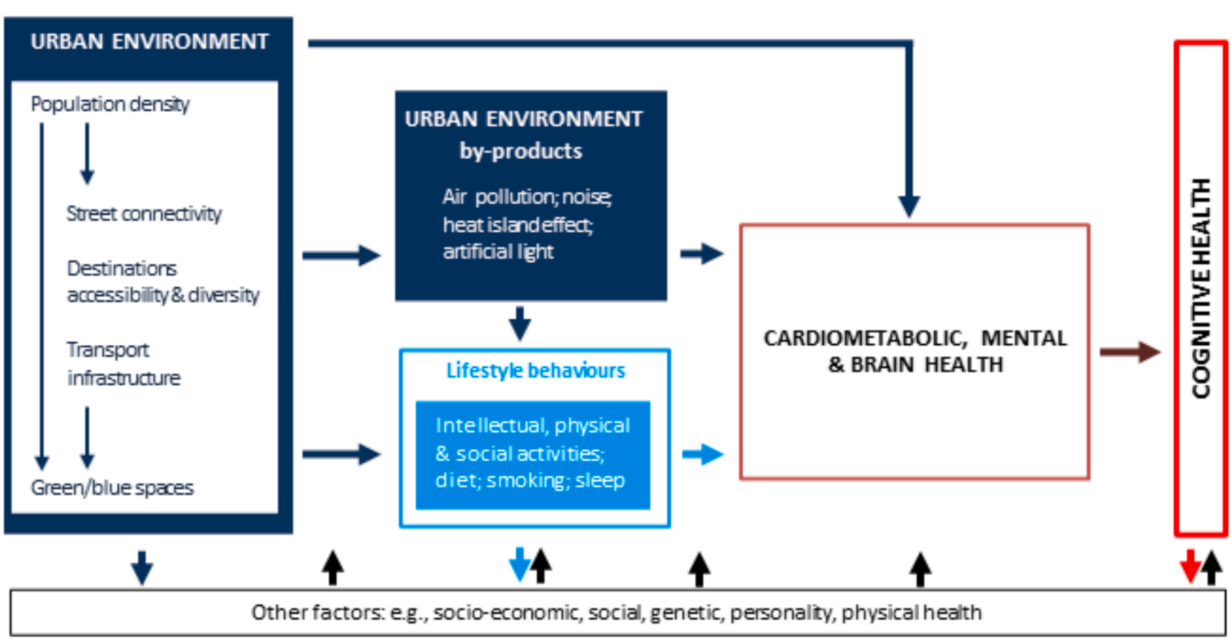

Fig. 1. A simplified ecological model of urban neighbourhood environmental influences on cognitive health.

Wu & Jackson, 2021; Zijlema et al., 2019).

Because urbanisation and associated built and natural environment features may simultaneously exert beneficial and harmful effects on cognitive health (Fig. 1), it is important to estimate their total (unadjusted for environmental mediators) as well as direct (adjusted for environmental mediators) and indirect (mediated) associations with cognitive health outcomes. However, only a few studies have done this, all of which were cross-sectional and focused on only a couple of facets of cognition (Cerin et al., 2021, 2022), and none examined transitions from normal cognition to MCI and/or dementia.

The current body of evidence in this field is also limited in both scope and methodological rigour. Most studies failed to consider all key categories of environmental attributes (Fig. 1) and adopt a causal inference framework, whereby plausible causal interrelationships between environmental attributes are considered in order to model causal assumptions and inform confounder selection for causal questions (Cerin et al., 2021, 2022). In addition, studies with cognitive assessments at multiple time points typically had one environmental assessment at baseline and, hence, were unable to estimate longitudinal environment-cognition relationships (i.e., if changes in the environment were associated with changes in cognition) (Clarke et al., 2015; Luo et al., 2019; Wörn et al., 2017). A study with multiple time points of environmental exposures examined the moderating effects of a single environmental attribute (i.e., greenness) on trajectories of cognitive decline but did not examine the extent to which changes in the environment result in changes in trajectories (de Keijzer et al., 2018). Finally, no studies examined built and natural environmental characteristics of conversion to and reversal from clinically determined cognitive impairments (e.g., MCI or dementia).

To address the abovementioned shortcomings and knowledge gaps, the aim of this population-based longitudinal study was to simultaneously estimate cross-sectional and longitudinal associations of the three main categories of neighbourhood environmental attributes (built and natural environments and urbanisation by-products) with multiple domains of cognitive function. In doing so, unlike previous longitudinal studies, we acknowledged the interrelationships between environmental characteristics (Fig. 1) and estimated total (unadjusted for environmental mediators), direct (adjusted for environmental mediators) and indirect (via environmental mediators) associations with cognitive health outcomes. We also examined the associations of neighbourhood attributes with conversion to and reversal from clinically determined MCI or dementia. This information is key for understanding how features of urban environments shape cognitive health in older populations. We hypothesised that living in neighbourhoods with higher levels of density, better access to a variety of destinations, greenspace and blue space, and lower concentrations of ambient air pollutants would be associated with better cognitive health (higher levels of, and slower declines in, cognitive functions). We also hypothesised that the direct effects of density and access to destinations on cognitive health would be positive and stronger than their corresponding total effects (unadjusted for natural environment features and ambient air pollution).

2. Materials and methods

2.1. Study design and procedure

We used data from the Personality and Total Health through life (PATH) project, one of the aims of which was to delineate the course of cognitive abilities across adulthood (Anstey et al., 2012). PATH was established in 1999, with baseline (Wave 1) assessments conducted in 2001 and 2002. It encompassed three cohorts aged 20–24, 40–44 and 60–64 years at baseline who were followed up for two decades. Participants were sampled randomly from the electoral rolls for Canberra (Australian Capital Territory) and Queanbeyan (New South Wales), which included nearly 95 % of Australian citizens aged 18+ years residing in the relevant electorates. Response rates ranged from 58.3 % to 64.6 % (Anstey et al., 2012). The study was approved by the Australian National University's Human Research Ethics Committee (Protocols: 2009/039; 2009/308; 2012/074; 2006/0314; 2002/0189) and written consent was obtained from all participants prior to data collection.

Assessments were conducted every four years – namely, in 2001–02 (Wave 1), 2005/06 (Wave 2), 2009/10 (Wave 3), 2013/15 (Wave 4) and 2017/19 (Wave 5). The present study focused on the 60+ years cohort with geocoded residential addresses (see *Participants* section below) and utilised data from the first four waves available to us. We focused on the 60+ years cohort because it was the only one that underwent in-depth neuropsychological and clinical assessments. Socio-demographic, psychosocial and most health-related data were collected using self-completed questionnaires on computers in the participants' homes (Anstey et al., 2012). Cognitive testing was performed by trained interviewers. At Waves 1 to 3, participants with poor performance on selected cognitive tests were invited to undergo a detailed neurocognitive assessment. Clinical diagnoses of MCI or dementia were performed using diagnostic criteria (see *Measures* section below) (Christensen et al., 2008). At Wave 4, due to the higher prevalence of cognitive impairment in the whole sample, a longer test battery was administered to the whole sample and an algorithm was applied to classify according to DSM diagnoses as described previously (Eramudugolla et al., 2017).

2.2. Participants

At Wave 1 (baseline), 2551 participants aged 60+ years were recruited and 2445 were successfully assessed. The participation rates with successful assessments at the subsequent three waves were 86.6 % (n = 2117), 80.7 % (n = 1872) and 63.6 % (n = 1555) relative to baseline. Fig. S1 provides more detailed information on the participation rates and reasons for loss to follow-up. Full residential addresses (including street number) were obtained from 1164 participants between Waves 4 and 5 (96.6 % of whom participated in Wave 4) along with information on whether they resided at a different address in prior waves. All except four of these full addresses could be geocoded. Hence, we developed neighbourhood spatial indicators for 1160 participants who constituted the analytical sample for the present study (see Fig. S3 for spatial distribution of participants). Differences between the analytical sample and participants excluded from the study due to not having complete residential address information are reported in Table S1.

2.3. Measures

2.3.1. Cognitive function (outcomes)

Several cognitive function outcomes were used because the literature suggests that the impacts of environmental attributes on cognitive health may differ by cognitive function domain (Besser et al., 2017; Cerin et al., 2021; Chen et al., 2022). The Digit Span Backward (DSB; Wechsler, 1945), a subset of the Wechsler Memory Scale (WMS-IV), was used to assess verbal working memory. Participants were presented with a sequence of digits increasing in length at the rate of one digit per second and, subsequently, participants were asked to repeat the digits in reverse order with which digits were presented. The number of correctly recalled digit sequences was an outcome measure. The Symbol Digit Modalities Test (SDMT; Smith, 1982) is a measure of attention and processing speed. Participants were given a coded key consisting of nine geometrical symbols, each representing a digit, and then they were asked to substitute as many digits for the symbols as possible in 90 s. Participants were given 10 practice items prior to the test. The final score was the correct number of substitutions and scores ranged from 0 to 110. The first list of the California Verbal Learning Test (CVLT; Delis et al., 1987) was used to assess verbal memory in older adults. In this test, participants were asked to listen to a list of 16 nouns and, subsequently, recall as many of the nouns as possible (immediate recall). After a distractor task, the participants were asked to recall the list a second time (delayed recall). The total number of words recalled correctly was an outcome measure and scores ranged from 0 to 16. For this study, we used the score on the immediate recall because the protocol of the delayed recall at Wave 4 differed from that at Waves 1 to 3. The Mini-Mental State Examination (MMSE; Folstein et al., 1975) was used to measure global cognitive function, with a score ranging from 0 to 30.

The neurocognitive battery results were used to screen for cognitive impairment and, subsequently, if participants met the predetermined cut-off scores, they were assigned for further neurocognitive and clinical assessments. Cognitive impairment was determined as a score below the 5th percentile score on neurocognitive tests relative to published age- and education-matched normative data (see Supplementary Material for further details). Participants who screened positive for cognitive impairment and consented to participate further, underwent a clinical interview and additional neuropsychological assessments (Anstey et al., 2012; Kumar et al., 2005). For the purpose of this study, we used the following classification according to DSM-4 criteria: no mild cognitive impairment, mild cognitive impairment (MCI) and dementia. Diagnoses were formulated using clinical checklists and established criteria as well as data from medical history and neuropsychological assessments (Anstey et al., 2012). Given the low frequencies of participants with MCI and dementia, for analytical purposes, a dichotomous variable of cognitive states wad created: no MCI/dementia vs. MCI/dementia.

2.4. Socio-demographic and health characteristics (covariates and confounders)

Several self-reported socio-demographic variables were included in the regression models as confounders or covariates (see *Statistical Analyses* section). These comprised sex, age at baseline, non-English-speaking background (yes vs. no), years of education, employment status (in part-time or full-time employment vs. not employed), home-ownership (yes vs. no), living with a partner (yes vs. no), residential mobility (stayer; moved to the current address before Wave 3; moved to the current address before Wave 4), and health conditions and behaviours considered to be risk factors for dementia (Livingston et al., 2020) but not mediators of the associations between the characteristics of the neighbourhood environment examined in this study and cognitive function (Cerin et al., 2020a). These confounders/covariates included hearing problems (yes vs. no), head injuries (no; yes; uncertain) and past (before baseline) alcohol consumption (abstain; occasional; light; medium; hazardous/harmful). Although data were available, hypertension, obesity, smoking status, current alcohol consumption, depression, physical activity and diabetes were not included in the regression models because they are potential mechanisms through which the neighbourhood environment may influence cognitive function in late life (Cerin et al., 2020a; Cerin et al., 2020b) while the aim of this study was to examine the confounder-adjusted total and direct (i.e., controlled for environmental mediators) associations of characteristics of the neighbourhood environment with cognitive function.

2.5. Attributes of the neighbourhood environment (exposures)

We geocoded participants' residential addresses at the building level. Participants were assigned the same geocoded address (as provided between Waves 4 and 5) for all time points. These included 860 participants who did not change residential address across the whole study (74.1 % of the sample), 146 participants who moved to the provided address before Wave 3 (12.6 %) and 154 (13.3 %) participants who moved to the provided address between Wave 3 and 4. This information (residential mobility) was included in the analyses (see Statistical Analyses section).

We created 1 km (radius) road network buffers around the participants' geocoded residential addresses (Adams et al., 2014; Frank et al., 2017) with ArcGIS v.10.6 network analyst toolbox (Environmental Systems Research Institute, 2021). These buffers used purpose-built pedestrian network paths and roads accessible to people. Roads devoted only to motorised vehicles (e.g., highways) were excluded. We chose a 1 km buffer radius because it is frequently used in international studies (Adams et al., 2014; Cerin et al., 2020b; Cochrane et al., 2019) and 1 km is the average distance that adults and older adults are willing to walk to and from destinations of daily living (e.g., grocery shops) for utilitarian purposes in Australia (Gunn et al., 2017; Jafari et al., 2023). Furthermore, studies have shown that the associations of attributes of the neighbourhood environment with cognition-related health outcomes (e.g., blood lipids) and behaviours (e.g., physical activity) in Australian mid-aged and older adults are typically stronger when measures of the neighbourhood environment are based on buffers with 1 km radius compared to buffers with smaller (e.g., 500 m) or larger (e.g., 1.6 km) radiuses (Cerin et al., 2024; Gunn et al., 2017). Given that PATH is a longitudinal study, we created residential buffers for two time points for which road network data were available, i.e., for the years 2006 (concurrent to Wave 2) and 2011 (corresponding to 1 year after Wave 3).

Five built environment spatial indicators were computed for each residential buffer. They included population density (persons/km^2), street intersection density (intersections/km^2), number of public transport stops (train stations and bus stops), percentage of commercial land and a non-commercial land use mix index. *Population density* (persons per km^2 of buffer area) estimates were based on the Australian Bureau of Statistics (ABS) Mesh Block data from the 2006 and 2011 Censuses (Australian Bureau of Statistics, 2011; Australian Bureau of Statistics, 2006). Mesh Blocks are the smallest administrative areas in Australia for which Census data are available. *Street intersection density,* defined as the number of $\geq$3-way intersections per km^2 buffer area, was computed using walkable road network data from the PSMA Australia's 2006 and 2011 Transport and Topography datasets (PSMA Australia Limited, 2011a; PSMA Australia Limited, 2006a). The *number of public transport stops* (transit points) within residential buffers was derived from two datasets. Data on railway stations were based on the PMSA Australia's 2006 and 2011 Transport and Topography datasets (PSMA Australia Limited, 2011b; PSMA Australia Limited, 2006b), while those on bus stops were obtained from the Public Transport Authority and open-data sources (e.g., OpenStreetMap and Google Maps), which had available data for 2012 only (Australian Capital Government, 2017; Geofabrik, 2018; Google Developers, 2023; Northern Territory Government, 2021; Open Data Transport New South Wales, 2017; South Australia Government, 2020; Victoria Government, 2023). The *percentage of commercial land* (retail and services) and the *non-commercial land use mix index* were computed using 2006 and 2011 ABS data on the main land use for Mesh Blocks (Australian Bureau of Statistics, 2011; Australian Bureau of Statistics, 2006). The latter spatial indicator was represented by a land use entropy score ranging from 0 to 1 (Frank et al., 2010) and quantifying the heterogeneity of five non-commercial land uses (residential, industrial, medical, educational and other land uses). Three natural environment spatial indicators were included in this study: *percentage of* residential buffer area covered by *parkland* and *presence of* waterbodies or *blue spaces* (e.g., lakes, coastlines and rivers) in the residential buffer derived from 2006 and 2011 ABS Mesh Block data (Australian Bureau of Statistics, 2011; Australian Bureau of Statistics, 2006) and Geofabric (Australian Bureau of Meteorology, 2022); and *percentage of* residential area with tree cover derived from PMSA Australia's 2018 Tree Raster dataset (PSMA Australia Limited, 2019).

This study used annual average $PM_{2.5}$ and NO_2 concentrations as indicators of ambient air pollution because they have been linked to cognitive health (Kilian & Kitazawa, 2018; Power et al., 2016) and data on other pollutants were not available to us. We assigned annual average $PM_{2.5}$ and NO_2 concentrations using two national-scale satellite-based land-use regression (LUR) models for Australia, gridded at ~100 ×

~100 m, for each calendar year during 2005–2018 inclusive (2005 was the full year of satellite NO_2 observations). The LUR models captured an estimated 81 % (RMSE: 1.4 ppb) of spatial variability in annual NO_2, and an estimated 63 % (RMSE: 1 μg/m^3) of spatial variability in annual $PM_{2.5}$ (Knibbs et al., 2014; Knibbs et al., 2018b). Both models undergo ongoing checking, updates and testing to incorporate new predictors and monitor data as needed, as well as validation against databases of historical or independent monitoring sites (sites not used to develop the models) (Knibbs et al., 2018a; Knibbs et al., 2018b). The NO_2 model captured up to 66 % of annual NO_2 (RMSE: 2 ppb) at independent validation sites (Knibbs et al., 2016), while the $PM_{2.5}$ model captured up to 52 % (RMSE: 1.2 μg/m^3) at independent sites (Knibbs et al., 2018a; Knibbs et al., 2018b). The underlying resolution is determined by the spatial variation of the least granular predictor, and in practice is up to ~100 m in urban areas and up to ~500 m in rural areas (Ahmed et al., 2022).The centroid of each ~100 m grid cell was used to estimate LUR predictions from the models, which included predictors on natural and anthropogenic features (including satellite estimates of NO_2 and $PM_{2.5}$) that have a plausible association (negative or positive) with $PM_{2.5}$ and/or NO_2, as measured by regulatory monitors using standard reference methods. The LUR estimates were linked to geocoded addresses based on the cell they were within.

As noted above, eight out of ten spatial indicators were constructed for two distinct time points (2006 and 2011/12). In contrast, tree cover was derived from a single 2018 dataset and the number of public transport stops consisted of a component (train stations) with data from two distinctive time points (2006 and 2012) and another (bus stops) representing aggregated data across a period from 2006 to 2018. For analytical purposes (see *Statistical Analyses* section), we computed person-level average exposures representing the average values of the spatial indicators across the two time points (2006 and 2011/2012) for those indicators with available data. For the spatial indicators with data at a single time point, we used the single-time point values as estimates of person-level exposure to the neighbourhood attributes they represented. For the spatial indicators with available data on two time points, we also created measures of within-person changes in exposures across time corresponding to the difference between the value of a spatial indicator at a specific time point and the person-level average on the same indicator. Spatial indicators based on datasets from the year 2006 were linked to PATH data from Wave 1 and 2, while those based on the years 2011/12 were linked to Wave 3 and 4. Here, it is important to note that although we had air pollution data for each wave of the study, we opted for the estimation of only two time points concurrent to those of data available for other environmental indicators to enable robust adjustment for the confounding effects of the built and natural environment on the associations between ambient air pollution and cognitive health.

2.6. Statistical analyses

Descriptive statistics (frequencies, percentages, means and standard deviations) were computed for all variables, as appropriate. Different statistical methods were used to examine environmental correlates of cognitive function and transitions to cognitive states.

Generalised additive mixed models (GAMMs; package 'mgcv' version 1.8.42 in R) allowing for possible environment-cognition and environment-environment curvilinear relationships and accounting for dependency in the panel data (Wood, 2017) were used to estimate associations of neighbourhood environmental attributes with scores on cognitive function tests. GAMMs with Gaussian variance and identity link functions were used to model the scores on all tests except for the MMSE because they were approximately normally distributed. The scores on the MMSE were highly negatively skewed and, consequently, were reverse scored and modelled using GAMMs with Gamma variance and logarithmic link function. All GAMMs had random intercepts at the participant level. Curvilinear associations were estimated using thin plate splines and evidence of curvilinearity was based on Akaike Information Criterion (AIC) values (Wood, 2017). A ≥5-unit difference in AIC between GAMM with a linear vs. curvilinear term was used as the criterion for model selection (Burnham & Anderson, 2002).

We first ran intercept-only GAMMs of cognitive function scores to estimate the participant-level and repeated measures variances. To estimate the trajectories of the cognitive test scores across time, we then added participants' exact age across the various assessments, centred at its lowest value (60 years). The effect of age (time) was allowed to vary across participants by modelling it as a person-level random slope. Both linear and quadratic effects of age were considered because declines in cognitive functions are sharper in older age groups (Zaninotto et al., 2018). Next, we added neighbourhood environment attributes to the models and associated confounders and covariates, which were determined using directed acyclic graphs (DAGs) informed by previous studies and the authors' expert knowledge (Fig. S2 and Table S3).

As noted earlier, neighbourhood environmental attributes included person-level average environmental exposures (allowing estimation of cross-sectional associations) and, for attributes with values at two time points, within-person deviations from the person-level average exposure representing within-person changes in exposure across time (allowing estimation of longitudinal associations as in 'fixed effect' models (Boone-Heinonen et al., 2010)). Thus, each GAMM estimated four types of environment-cognition effects (Fig. 2):

(1) association(s) of person-level average environmental exposure(s) with person-level average cognitive function, quantified by the main effect(s) of average environmental exposure(s) on cognitive function – depicted in Fig. 2, panel A.
(2) associations of person-level average environmental exposure(s) with person-level trajectories of cognitive function, quantified by the interaction term of person-level average environmental exposure(s) by time (age centred at 60 years) in relation to cognitive function – depicted in Fig. 2, panel B.
(3) associations of within-person change in environmental exposure (s) with within-person change in cognitive function, quantified by the main effect(s) of within-person change in environmental exposure(s) on cognitive function – depicted in Fig. 2, panel C.
(4) association of within-person change in environmental exposure (s) with within-person changes in trajectory of cognitive function, quantified by the interaction term of within-person change in environmental exposure(s) by time in relation to cognitive function – depicted in Fig. 2, panel D.

Only statistically significant environmental attribute by time interaction terms ($p < 0.05$) were retained in the final GAMMs. The above-described modelling approach was employed to estimate confounder-adjusted total as well as direct effect (i.e., fully adjusted, controlled for environmental mediators) models of associations of neighbourhood environmental attributes with cognitive test scores. In line with the proposed model of cognitive health (Fig. 1 and Fig. S1), we also estimated the interrelationships between environmental attributes as supplementary analyses to allow for an examination of the indirect effects of environmental attributes on cognitive health.

Multi-state hidden Markov models with continuous time (Jackson, 2011) (package 'msm' version 1.7 in R) were used to estimate the associations between neighbourhood environmental attributes and the risk of the following transition states, noting that transitions from dementia to no MCI are not considered plausible (Salazar et al., 2007): from no MCI to MCI or worse (dementia); from MCI to no MCI. Death could not be considered as an absorbing state in the multi-state models because there were no confirmed deaths in the analytical sample across the study period (i.e., all participants in the analytic sample were alive in Wave 5 of the study). Given the low number of cases with cognitive impairment (Table 1), only total effect multi-state models for average environmental exposures could be estimated adjusted for confounders and covariates (Table S3).

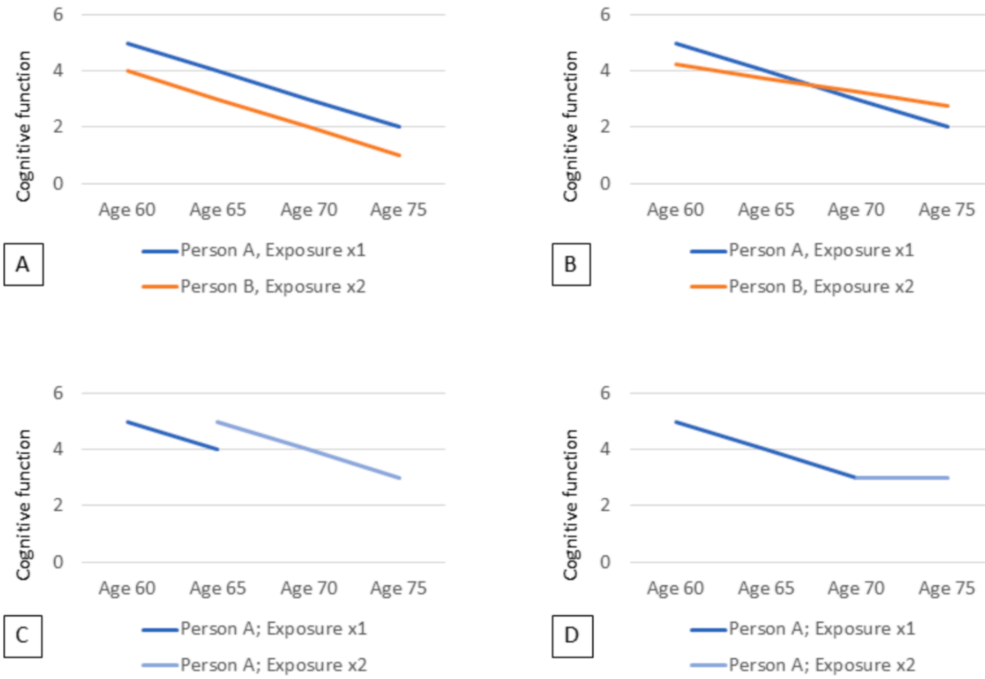

Fig. 2. Interpretation of effects of neighbourhood environmental attributes on cognitive function examined in this study. Panel A: person-level average exposure as a correlate of person-level cognitive function; panel B: person-level average exposure as a correlate of person-level trajectories of cognitive function (i.e., exposure as a moderator of trajectories); panel C: within-person change in exposure as a correlate of within-person change in cognitive function level; panel D: within-person change in exposure as a correlate of within-person changes in trajectory of cognitive function (i.e., change in exposure as a moderator of trajectories). Exposure level x_2 is presented as being more beneficial than x_1 in all graphs except for panel A.

Table 1
Socio-demographic and health-related characteristics of the analytical sample by study wave.

Characteristics	Wave 1 (n = 1160)	Wave 2 (n = 1160)	Wave 3 (n = 1158)	Wave 4 (n = 1124)
Sex, female, %	47.7	47.7	47.7	47.8
Age, years, M ± SD	62.4±1.5	66.5±1.5	70.5±1.5	75.0±1.5
Years of education	14.3±2.6	14.3±2.6	14.3±2.6	14.3±2.6
Tertiary education, %	43.9	43.9	44.0	44.2
Employed (part-time or full-time), %	46.7	29.0	19.1	10.9
Homeowner, %	91.3	92.3	92.4	90.1
Financial problems, %	10.3	7.9	6.2	5.8
Living with partner, %	80.0	78.6	73.2	69.4
English speaking background, %	93.1	93.1	93.1	93.3
Past (before baseline) alcohol intake, %				
Abstain	4.1	4.1	4.1	4.0
Occasional	21.0	21.0	20.9	20.6
Light	33.9	33.9	33.9	33.9
Medium	24.1	24.1	24.2	24.4
Hazardous/harmful	17.0	17.0	17.0	17.0
Hearing loss, %	0.8	11.0	12.4	12.6
Severe head injury (since previous assessment), %				
No	91.6	92.2	99.1	99.0
Yes	5.1	6.9	1.0	1.0
Unsure	3.4	0.9	0.0	0.0
Cognitive state, %				
No MCI	98.8	99.0	99.0	92.9
MCI	1.2	1.0	1.0	7.0
Dementia	0.0	0.0	0.0	0.1
Cognitive function tests, M ± SD				
CVLT – immediate recall	7.6±2.2	7.2±2.2	7.0±2.2	5.5±1.9
Digit span backward	5.3±2.2	5.4±2.2	5.3±2.2	5.5±2.2
Mini Mental State Examination	29.4±1.0	29.4±1.0	29.3±1.0	29.1±1.3
Symbol Digit Modalities Test	52.1±8.6	51.5±8.5	49.6±8.4	47.5±8.9

Notes. CVLT, California Verbal Learning Test; MCI, mild cognitive impairment, number of participants; M, mean; SD, standard deviation. Participants' sex is defined in biological terms.

All multi-state hidden Markov models and GAMMs were inverse probability weighted to account for selection bias in the analytic sample. Inverse probability weights were created by calculating the inverse of the conditional probability (or propensity score) of being included in the analytic sample given participants' characteristics at baseline as detailed in the Supplementary Material (p. 2). Residential mobility (stayer, mover) was considered as a moderator of the associations between exposures and outcomes in all models and, when statistically significant ($p < 0.05$), regression coefficients for stayers and movers were estimated. Multicollinearity was determined based on Variance Inflation Factor (VIF) values of variables included in the regression models. No adjustment for multiple comparisons was employed because the analyses were hypothesis-driven (Michels and Rosner, 1996; Rothman, 1990). All analyses were conducted in R 4.3.2 (R Core Team, 2023).

3. Results

3.1. Characteristics of the sample and neighbourhood attributes

Participants in the analytic sample were younger, more educated, more physically active, cognitively healthier, less likely to be hypertensive but more likely to be current smokers, diabetics and report better quality of life than their counterparts (Table S1). Table 1 reports the socio-demographic and health-related characteristics of the analytic sample. All participants had valid assessments at Waves 1 and 2, while 2 participants did not participate in Wave 3, and 36 participants did not participate in Wave 4. The analytical sample was balanced by sex, had an average age of 62.4 years at baseline, and consisted mostly of homeowners and individuals from an English-speaking background. Around 40 % of the sample had tertiary education. While nearly half of the sample was employed at baseline, the percentage of employed participants gradually decreased to reach 10.9 % in Wave 4. Similarly, the percentage of participants living with their partner decreased from 80 % at baseline to 69.4 % at Wave 4. Most participants reported being light consumers of alcohol before Wave 1 and not having had serious head injuries or hearing problems (Table 1).

Over 98 % of participants did not have MCI or dementia at Waves 1 to 3 (Table 1), while at Wave 4 the percentage dropped below 93 % (Table 1). At Wave 4, only one participant transitioned to dementia. Across the study, there were 90 transitions to worse cognitive states (i.e., from no MCI to MCI/dementia) and 25 transitions to better cognitive states (from MCI to no MCI) (Table S4). The average scores on the digit span backward test remained relatively stable across time, while those on the other tests decreased (Table 1).

Nearly 75 % of the analytical sample (n = 860) remained in the same neighbourhood across all four waves of the study, 12.6 % (n = 146) moved address before Wave 3 and 13.3 % (n = 154) before Wave 4. Differences between participants who stayed in their neighbourhood and those who moved to other neighbourhoods during the study are reported in the Supplementary Material (Table S2).

Table 2 reports the descriptive statistics of neighbourhood environmental attributes (exposures) at different time points as well as their average values and differences across time points. On average, the percentage of commercial land within residential buffers was low (~3%) as was non-commercial land use mix (a mean of 0.11 on a theoretical range of values from 0 to 1), while the percentages of buffer areas allocated to parkland and with tree cover were substantially higher (~15 % and 27 %, respectively). A quarter of participants had access to blue spaces within 1 km from home. Substantial variability across participants, here defined as a coefficient of variation exceeding 60 %, was observed for number of transit points, percentage of commercial land and parkland, presence of blue space, and non-commercial land use mix. In general, the levels of variability of neighbourhood attributes across time (i.e., differences between years) were smaller than those across participants. Non-commercial land use mix was the only exception, with a standard deviation of the difference between time points (years) being 2.5 times the standard deviation of the average values across years (Table 2).

3.2. Neighbourhood environmental attributes and cognitive function test scores

Table 3 shows the results of the total and direct main effect regression models of neighbourhood environmental attributes in relation to scores on cognitive function tests, while the moderating effects of neighbourhood environmental attributes on trajectories of cognitive function test scores across time are reported in Table 4, Tables S5 and S7, and Figs. 3 and 4, Figs. S13 and S14. The interrelationships between environmental attributes are depicted by Figs. S4-S12. In the remainder of the Results section, we use the term 'neighbourhood attribute' (e.g., population density) to refer to 'person-level average neighbourhood attribute' (e.g., person-level average population density) and 'change in neighbourhood attribute' (e.g., change in population density) to refer to 'within-person difference (change from Waves 1–2 to Wave 3–4) in neighbourhood environmental attribute'. Residential mobility was not a moderator of any examined environment-cognition association (all $ps > 0.390$). All VIFs were smaller than 2.61, indicating that multicollinearity was not an issue (Sheather, 2009).

Higher *population density* was associated with a lower average digit span backwards score (verbal working memory) (Table 3) and an increase in population density was predictive of a worse trajectory of performance on the same test (Table 4 and Table S7). However, only the latter effect remained statistically significant in the direct effect models (i.e., after adjustment for all environmental attributes). Population density also moderated the trajectory of SDMT scores (processing speed). While higher population density was associated with a steeper decline in SDMT scores from 60 to 70 years of age, it was associated with a slower decline from 70 to 75 years (Fig. 4 and Fig. S14, panels A). This

Table 2
Descriptive statistics (M ± SD) of neighbourhood environmental attributes.

Attribute	Year 2006[1]	Year 2011/12[2]	Average across years	Difference between years
Population density (people/km^2)	1573±704	1662±724	1617±703	89±248
Street intersection density (intersections/km^2)	51.3±16.6	59.6±18.2	55.4±16.6	8.4±10.7
Transit points (train stations and bus stops)[3]	12.2±7.8	12.2±7.8	12.2±7.8	0.003±0.06
Commercial land (% within 1 km buffer)	3.12±7.90	3.14±8.17	3.13±7.97	0.02±2.07
Non-commercial land use mix	0.13±0.11	0.13±0.11	0.13±0.11	0.001±0.28
Parkland (% within 1 km buffer)	18.5±12.7	17.8±12.0	18.1±12.2	−0.62 ± 4.11
Tree cover (% within 1 km buffer)[4]	26.5±9.0	26.5±9.0	26.5±9.0	0.0±0.0
Blue space (presence within 1 km)	0.25±0.43	0.25±0.43	0.25±0.43	−0.003 ± 0.14
$PM_{2.5}$ (μg/m^3)	8.79±1.76	6.70±1.10	7.74±1.39	−2.09 ± 0.90
NO_2 (ppb)	4.12±2.08	3.39±1.79	3.75±1.93	−0.73 ± 0.44
Area-level SEIFA	1065±110	1021±127	1043±109	−43 ± 95

Notes. M, mean; SD, standard deviation; SEIFA, Socio-Economic Indexes for Areas; $PM_{2.5}$, particulate matter with a diameter of 2.5 μm (micrometres) or smaller; NO_2, nitrogen dioxide; ppb, parts per billion. [1] linked to Waves 1 and 2 of PATH survey data. [2] linked to Waves 3 and 4 of PATH survey data. [3] train stations data obtained for years 2006 and 2011/12, bus stations data obtained for 2012. [4] data available for 2018 only.

Table 3
Total and direct associations of neighbourhood environmental attributes with cognitive function.

	Mod	CVLT – immediate recall	Digit span backwards	SDMT	MMSE
Between-person SD	E	1.38	1.71	7.36	1.56
Within-person SD	E	2.57	2.03	7.10	1.76
Neighbourhood environmental attribute		*b* (95 % CI)	*b* (95 % CI)	*b* (95 % CI)	e^b (95 % CI)
Population density (1000 persons/km^2)					
Person-level average	T	−0.078 (−0.206, 0.050)	−0.216 (−0.365, −0.067)	−0.277 (−0.897, 0.342)	1.012 (0.890, 1.150)
	D	−0.196 (−0.405, 0.012)	−0.141 (−0.329, 0.047)	−0.339 (−1.144, 0.466)	0.834 (0.675, 1.030)
Within-person difference (change from W1-2 to W3-4)	T	−0.409 (−0.788, −0.031)	0.018 (−0.328, 0.364)	0.080 (−1.060, 1.219)	1.480 (1.030, 2.126)
	D	−0.301 (−0.700, 0.097)	0.059 (−0.313, 0.431)	−0.071 (−1.285, 1.146)	1.473 (1.006, 2.169)
Street intersection density (intersections/km^2)					
Person-level average	T	0.001 (−0.006, 0.008)	0.003 (−0.007, 0.013)	0.041 (0.007, 0.075)	1.015 (1.006, 1.025)
	D	0.0004 (−0.007, 0.008)	0.008 (−0.004, 0.019)	0.046 (0.010, 0.083)	1.010 (1.002, 1.019)
Within-person difference (change from W1-2 to W3-4)	T	−0.001 (−0.009, 0.007)	0.010 (0.001, 0.020)	0.028 (0.004, 0.053)	1.001 (0.991, 1.011)
	D	0.003 (−0.006, 0.012)	0.001 (−0.010, 0.012)	0.027 (0.0004, 0.054)	0.998 (0.986, 1.009)
Transit points (train stations and bus stops)					
Person-level average	T	0.003 (−0.010, 0.015)	0.005 (−0.010, 0.020)	0.048 (−0.014, 0.111)	1.009 (0.997, 1.022)
	D	−0.002 (−0.016, 0.013)	0.008 (−0.009, 0.024)	0.024 (−0.045, 0.093)	1.002 (0.995, 1.008)
Within-person difference (change from W1-2 to W3-4)	T	$-5.80 \cdot 10^{-5}$ ($1.57 \cdot 10^{-4}$, $4.14 \cdot 10^{-5}$)	−0.0001 (−0.0002, −0.00005)	−0.415 (−5.596, 4.766)	5.419 (1.031, 28.473)
	D	$-6.82 \cdot 10^{-5}$ ($1.68 \cdot 10^{-4}$, $3.14 \cdot 10^{-5}$)	−0.0002 (−0.0002, −0.00006)	−0.318 (−5.544, 4.907)	1.535 (0.494, 4.769)
Commercial land (% within 1 k m buffer)					
Person-level average	T	0.002 (−0.010, 0.013)	0.010 (−0.003, 0.023)	0.010 (−0.045, 0.064)	1.018 (1.006, 1.030)
	D	−0.001 (−0.013, 0.012)	0.009 (−0.006, 0.024)	−0.014 (−0.074, 0.045)	1.018 (1.004, 1.032)
Within-person difference (change from W1-2 to W3-4)	T	−0.002 (−0.048, 0.044)	−0.005 (−0.048, 0.037)	−0.036 (−0.173, 0.102)	1.034 (0.976, 1.095)
	D	0.006 (−0.041, 0.052)	0.003 (−0.040, 0.045)	−0.036 (−0.176, 0.103)	1.035 (0.976, 1.097)
Non-commercial land use mix (unit * 10)					
Person-level average	T	0.042 (−0.036, 0.121)	−0.042 (−0.134, 0.051)	0.490 (1.255, 0.855)	1.034 (0.956, 1.118)
	D	0.021 (−0.065, 0.108)	−0.073 (−0.174, 0.029)	0.426 (0.047, 0.805)	1.024 (0.949, 1.106)
Within-person difference (change from W1-2 to W3-4)	T	−0.199 (−0.554, 0.156)	0.198 (−0.127, 0.522)	0.531 (−0.172, 1.234)	1.174 (0.905, 1.328)
	D	−0.219 (−0.578, 0.140)	0.204 (−0.122, 0.521)	0.752 (0.040, 1.464)	1.180 (1.019, 1.367)
Parkland (% within 1 km buffer)					
Person-level average	T	−0.009 (−0.018, −0.001)	−0.003 (−0.113, 0.006)	−0.003 (−0.040, 0.033)	1.002 (0.994, 1.009)
	D	−0.010 (−0.019, −0.001)	−0.001 (−0.011, 0.008)	−0.017 (−0.057, 0.023)	1.000 (0.992, 1.008)
Within-person difference (change from W1-2 to W3-4)	T	0.037 (0.011, 0.063)	0.003 (−0.019, 0.025)	0.027 (−0.044, 0.098)	1.004 (0.983, 1.025)
	D	0.030 (0.004, 0.056)	0.011 (−0.011, 0.033)	0.050 (−0.023, 0.123)	1.002 (0.981, 1.024)
Tree cover (% within 1 km buffer)					
Person-level average	T	0.008 (−0.002, 0.019)	−0.006 (−0.018, 0.006)	−0.008 (−0.059, 0.044)	1.012 (1.001, 1.022)
	D	0.011 (0.001, 0.021)	−0.009 (−0.022, 0.005)	−0.002 (−0.054, 0.051)	1.007 (0.996, 1.018)
Within-person difference (change from W1-2 to W3-4)	T	NA	NA	NA	NA
	D	NA	NA	NA	NA
Blue space (presence within 1 km)					
Person-level average	T	0.026 (−0.265, 0.317)	−0.084 (−0.353, 0.186)	2.029 (0.613, 3.445)	0.852 (0.668, 1.071)
	D	0.067 (−0.230, 0.365)	−0.142 (−0.428, 0.144)	1.985 (0.521, 3.448)	0.861 (0.674 1.100)
Within-person difference (change from W1-2 to W3-4)	T	0.138 (−0.630, 0.907)	−0.370 (−0.935, 0.195)	1.678 (−0.605, 3.961)	0.751 (0.409, 1.380)
	D	0.469 (−0.311, 1.250)	−0.462 (−1.025, 1.020)	2.063 (−0.239, 4.365)	0.784 (0.425, 1.447)
$PM_{2.5}$ (μg/m^3)					
Person-level average	T	−0.009 (−0.102, 0.084)	−0.071 (−0.160, 0.018)	−0.102 (−0.474, 0.270)	1.008 (0.933, 1.088)
	D	0.033 (−0.043, 0.108)	−0.079 (−0.171, 0.013)	−0.152 (−0.514, 0.210)	0.980 (0.905, 1.062)
Within-person difference (change from W1-2 to W3-4)	T	−0.181 (−0.538, 0.176)	−0.131 (−0.199, −0.063)	−0.186 (−0.403, 0.031)	0.929 (0.867, 0.995)
	D	0.076 (−0.014, 0.166)	−0.177 (−0.262, −0.091)	−0.085 (−0.358, 0.188)	0.949 (0.867, 1.039)
NO_2 (ppb)					

(*continued on next page*)

Table 3 (*continued*)

	Mod	CVLT – immediate recall	Digit span backwards	SDMT	MMSE
Between-person SD	E	1.38	1.71	7.36	1.56
Within-person SD	E	2.57	2.03	7.10	1.76
Neighbourhood environmental attribute		*b* (95 % CI)	*b* (95 % CI)	*b* (95 % CI)	e^b (95 % CI)
Person-level average	T	0.044 (−0.018, 0.107)	0.041 (−0.033, 0.115)	−0.037 (−0.345, 0.270)	1.019 (0.956, 1.086)
	D	0.044 (−0.018, 0.107)	0.035 (−0.039, 0.108)	−0.064 (−0.368, 0.240)	1.019 (0.956, 1.087)
Within-person difference (change from W1-2 to W3-4)	T	0.154 (−0.024, 0.332)	−0.075 (−0.246, 0.097)	−0.593 (−1.141, −0.044)	0.899 (0.757, 1.067)
	D	0.059 (−0.162, 0.279)	0.167 (−0.035, 0.368)	−0.287 (−0.965, 0.391)	1.052 (0.849, 1.306)

Notes. E, empty model (intercept only model with no covariates); T, total effect model; D, direct effect model; W, wave; *b*, regression coefficient; e^b, exponentiated regression coefficient; CI, confidence interval; Mod, model; CVLT, California Verbal Learning Test; SDMT, Symbol Digit Modalities Test; MMSE, Mini Mental State Examination; $PM_{2.5}$, particulate matter with a diameter of 2.5 μm (micrometres) or smaller; NO_2, nitrogen dioxide; ppb, parts per billion; NA, not applicable as only data for one time point available.

moderating effect was stronger upon adjustment for all environmental attributes (Fig. 4, panel A) than only environmental confounders (Fig. S14, panel A) (Table S5 and Table S7). An increase in population density was associated with an increase in MMSE score (global cognition) and a decrease in CVLT – immediate recall (verbal memory) (Table 3). The latter association was substantially attenuated and not statistically significant in the direct effect model.

Higher *street intersection density* was associated with higher average SDMT (processing speed) and MMSE (global cognition) scores (Table 3), slower declines in MMSE (in the total effect model only) (Table 4 and Table S7) and SDMT scores but only from 60 to 70 years of age (Fig. 4 and Fig. S14; panels B). From 70 to 75 years of age, higher street intersection density was predictive of a steeper decline in SDMT scores, yielding no difference in average scores between participants living in neighbourhoods with above and below average street intersection density (Fig. 4 and Fig. S14; panels B). An increase in street intersection density was also coupled with an increase in SDMT score (processing speed) and digit span backwards (verbal working memory) (total effect model only) (Table 3). Fewer associations between *number of transit points* and cognitive function test scores were observed. Having more transit points in the neighbourhood was predictive of a slower decline in MMSE scores (global cognition) and an increase in the same attribute was associated with an increase in MMSE score. However, both associations were statistically significant in the total effect models only (Table 3). An increase in transit points was also associated with a decrease in digit span backwards (verbal working memory) (Table 3).

Living in an area with more *commercial land* was associated with higher MMSE scores (global cognition) (Table 3) as well as a slower decline in performance in the MMSE (Table 4 and Table S7). In contrast, an increase in commercial land was predictive of a steeper decline in MMSE scores (Table 4 and Table S7). The opposite was observed for the digit span backwards test (verbal working memory) (Table 4 and Table S7). *Non-commercial land use mix* was positively related to average SDMT scores (processing speed) and an increase in the same neighbourhood attribute was associated with increases in both SDMT (processing speed) and MMSE (global cognition) scores (Table 3). Having more *parkland* in the neighbourhood was associated with a lower score on the CVLT −immediate recall test (verbal working memory). However, an increase in the same attribute was predictive of improved performance on the same test. *Tree cover* was also positively related to scores on the CVLT – immediate recall test. The same held true for MMSE, although only in the total effect models (Table 3). While participants with better access to *blue spaces* had higher SDMT scores (processing speed) (Table 3), they showed a steeper decline in CVLT – immediate recall (verbal working memory).

Higher *annual average $PM_{2.5}$ concentrations* were accompanied by steeper declines in digit span backward (verbal working memory) (Table 4 and Table S7) and SDMT (processing speed) scores (Fig. 4 and Fig. S14, panels C), while increases in $PM_{2.5}$ concentrations were associated with a decrease and steeper decline in digit span backwards as well as a decrease in MMSE (global cognition) score (in total effect models only) (Tables 3 and 4 and Table S7). Increases in *annual average NO_2 concentrations* were predictive of a decrease in SDMT (processing speed) score (Table 3; total effect model only) and steeper declines in performance on the MMSE (global cognition) (Table 4 and Table S7). Increases in annual average NO_2 concentrations were also associated with a steeper decline in CVLT – immediate recall (verbal working memory) from 70 to 75 years of age (Fig. 3 and Fig. S13).

3.3. Neighbourhood environmental correlates of transition to cognitive states

The total effects of neighbourhood environmental attributes on transitions to/from various cognitive states are reported in Table 5. Participants living in more dense neighbourhoods with more transit points, commercial land and parkland, higher levels of non-commercial land use mix and access to blue spaces were less likely to transition from no MCI to MCI/dementia. Conversely, those living in neighbourhoods with higher average annual concentrations of NO_2 were more likely to transition to MCI/dementia. Three (population density; transit points and non-commercial land use) out of five built environment attributes were associated with a lower likelihood of transitioning back to a better cognitive state.

4. Discussion

We examined the relationships of a comprehensive set of interrelated neighbourhood environmental attributes, encompassing the built and natural environment as well as ambient air pollution, with cognitive health outcomes in a population-based cohort of Australian older urban dwellers. In doing so, we distinguished the effects of average environmental exposures (person-level average exposure) from those of environmental changes (within-person changes in exposures) on cognitive function. This analytical approach can help quantify the potential long-term and medium-term impacts of residential environments on cognitive health. Furthermore, an analysis of longitudinal associations addresses, in part, person-level sources of bias, such as residential self-selection and other person-level confounders (Boone-Heinonen et al., 2010).

In general, we found that, apart from population density, aspects of neighbourhood walkability (i.e., street connectivity, access to commercial and non-commercial services, public transport) and the natural environment (e.g., tree cover and blue space) tended to be associated

Table 4
Moderating effects of neighbourhood environmental attributes on trajectories of cognitive function test scores (linear time trends)*.

Environmental attribute (EA)	Cognitive function test	Model	Effect	Reg. term	Point estimate (95 % CI)	p-value
Population density (1000 persons/km^2) – within-person difference (change from W 1–2 to W 3–4)	Digit span backwards	D	Age_{60} @ 1 SD decrease in EA	b	0.047 (0.025, 0.069)	<0.001
		D	Age_{60} @ no change in EA	b	0.028 (0.011, 0.045)	0.001
		D	Age_{60} @ 1 SD increase in EA	b	0.009 (−0.013, 0.031)	0.430
Street intersection density (intersections/km^2) – person-level average	MMSE	T	Age_{60} @ 1 SD below mean EA	e^b	0.924 (0.909, 0.940)	<0.001
		T	Age_{60} @ mean EA	e^b	0.936 (0.923, 0.949)	<0.001
		T	Age_{60} @ 1 SD above mean EA	e^b	0.948 (0.930, 0.966)	<0.001
Transit points (train stations and bus stops) – person-level average	MMSE	T	Age_{60} @ 1 SD below mean EA	e^b	0.924 (0.900, 0.939)	<0.001
		T	Age_{60} @ mean EA	e^b	0.934 (0.923, 0.945)	<0.001
		T	Age_{60} @ 1 SD above mean EA	e^b	0.944 (0.930, 0.960)	<0.001
Commercial land (% within 1 km buffer) – within-person difference (change from W 1–2 to W 3–4)	Digit span backwards	T	Age_{60} @ 1 SD decrease in EA	b	−0.001 (−0.019, 0.016)	0.872
		T	Age_{60} @ no change in EA	b	0.011 (0.0001, 0.023)	0.047
		T	Age_{60} @ 1 SD increase in EA	b	0.025 (0.007, 0.043)	0.006
Commercial land (% within 1 km buffer) – person-level average	MMSE	D	Age_{60} @ 1 SD below mean EA	e^b	0.935 (0.917, 0.954)	<0.001
		D	Age_{60} @ mean EA	e^b	0.949 (0.934, 0.965)	<0.001
		D	Age_{60} @ 1 SD above mean EA	e^b	0.963 (0.949, 0.983)	<0.001
Commercial land (% within 1 km buffer) – within-person difference (change from W 1–2 to W 3–4)	MMSE	D	Age_{60} @ 1 SD decrease in EA	e^b	0.967 (0.947, 0.988)	0.002
		D	Age_{60} @ no change in EA	e^b	0.949 (0.934, 0.965)	<0.001
		D	Age_{60} @ 1 SD increase in EA	e^b	0.931 (0.912, 0.951)	<0.001
Tree cover (% within 1 km buffer) – person-level average	Digit span backwards	T	Age_{60} @ 1 SD below mean EA	b	0.021 (0.007, 0.034)	0.003
		T	Age_{60} @ mean EA	b	0.010 (−0.001, 0.021)	0.082
		T	Age_{60} @ 1 SD above mean EA	b	−0.001 (−0.017, 0.015)	0.933
Tree cover (% within 1 km buffer) – person-level average	MMSE	D	Age_{60} @ 1 SD below mean EA	e^b	0.939 (0.921, 0.956)	<0.001
		D	Age_{60} @ mean EA	e^b	0.952 (0.936, 0.968)	<0.001
		D	Age_{60} @ 1 SD above mean EA	e^b	0.966 (0.944, 0.987)	0.002
Blue space (presence within 1 km buffer) – person-level average	MMSE	D	Age_{60} @ 1 SD below mean EA	e^b	0.961 (0.938, 0.984)	0.001
		D	Age_{60} @ mean EA	e^b	0.945 (0.927, 0.963)	<0.001
		D	Age_{60} @ 1 SD above mean EA	e^b	0.930 (0.909, 0.952)	<0.001
$PM_{2.5}$ (μg/m^3) – person-level average	Digit span backwards	D	Age_{60} @ 1 SD below mean EA	b	0.042 (0.024, 0.060)	<0.001
		D	Age_{60} @ mean EA	b	0.030 (0.013, 0.047)	<0.001

(*continued on next page*)

Table 4 (*continued*)

Environmental attribute (EA)	Cognitive function test	Model	Effect	Reg. term	Point estimate (95 % CI)	*p*-value
		D	Age_{60} @ 1 SD above mean EA	*b*	0.018 (−0.004, 0.040)	0.116
$PM_{2.5}$ ($\mu g/m^3$) – within-person difference (change from W 1–2 to W 3–4)	Digit span backwards	D	Age_{60} @ 1 SD decrease in EA	*b*	0.049 (0.024, 0.073)	<0.001
		D	Age_{60} @ no change in EA	*b*	0.030 (0.013, 0.047)	<0.001
		D	Age_{60} @ 1 SD increase in EA	*b*	0.011 (−0.011, 0.033)	0.324
NO_2 (ppb) – within-person difference (change from W 1–2 to W 3–4)	MMSE	D	Age_{60} @ 1 SD decrease in EA	e^b	1.007 (0.972, 1.042)	0.713
		D	Age_{60} @ no change in EA	e^b	0.945 (0.927, 0.964)	<0.001
		D	Age_{60} @ 1 SD increase in EA	e^b	0.888 (0.857, 0.920)	<0.001

Note. T, total effect model; D, direct effect model; W, wave; *b*, regression coefficient; e^b, exponentiated regression coefficient; CI, confidence interval; Mod, model; CVLT, California Verbal Learning Test; SDMT, Symbol Digit Modalities Test; MMSE, Mini Mental State Examination; $PM_{2.5}$, particulate matter with a diameter of 2.5 µm (micrometres) or smaller; NO_2, nitrogen dioxide; ppb, parts per billion; Age_{60}, age centred at 60 years; SD, standard deviation; Reg. term, Regression term. *estimates of total effect models are presented only if those of the corresponding direct effect models were not statistically significant.

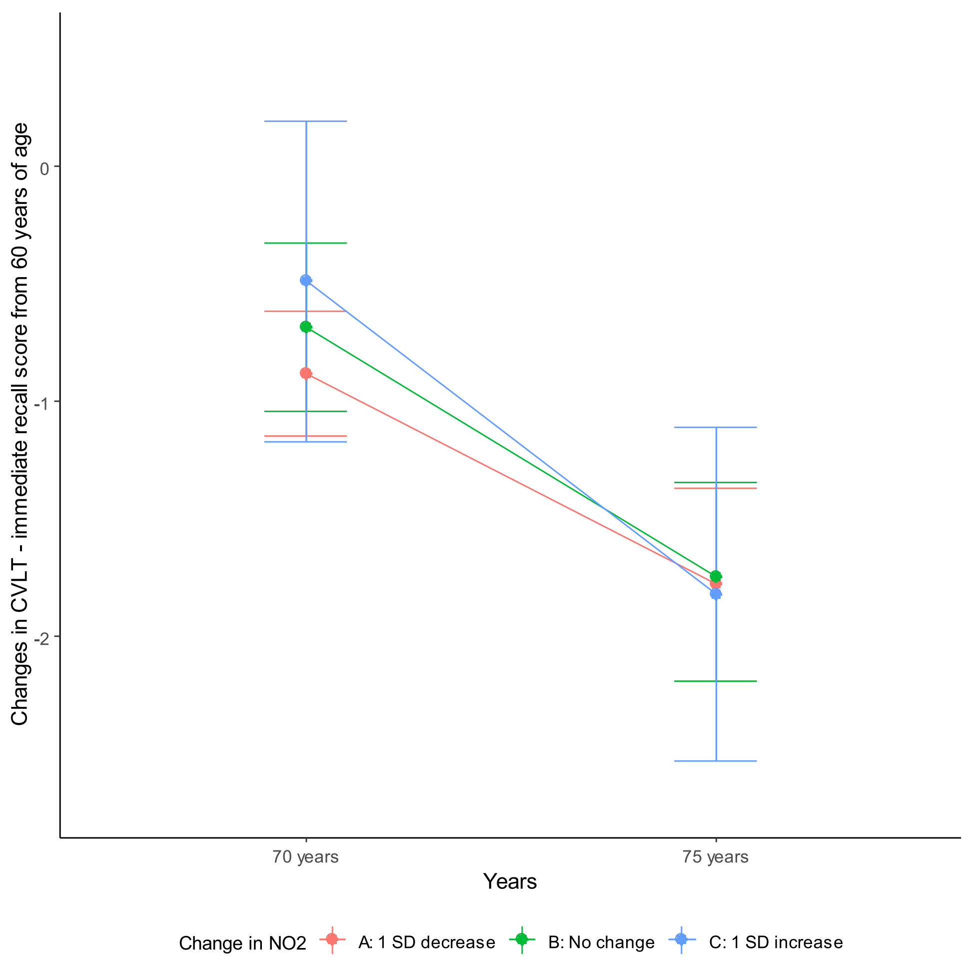

Fig. 3. Moderating effects of changes in annual average concentrations of NO_2 on changes in CVLT – immediate recall score from 60 years of age (direct effect model estimates).

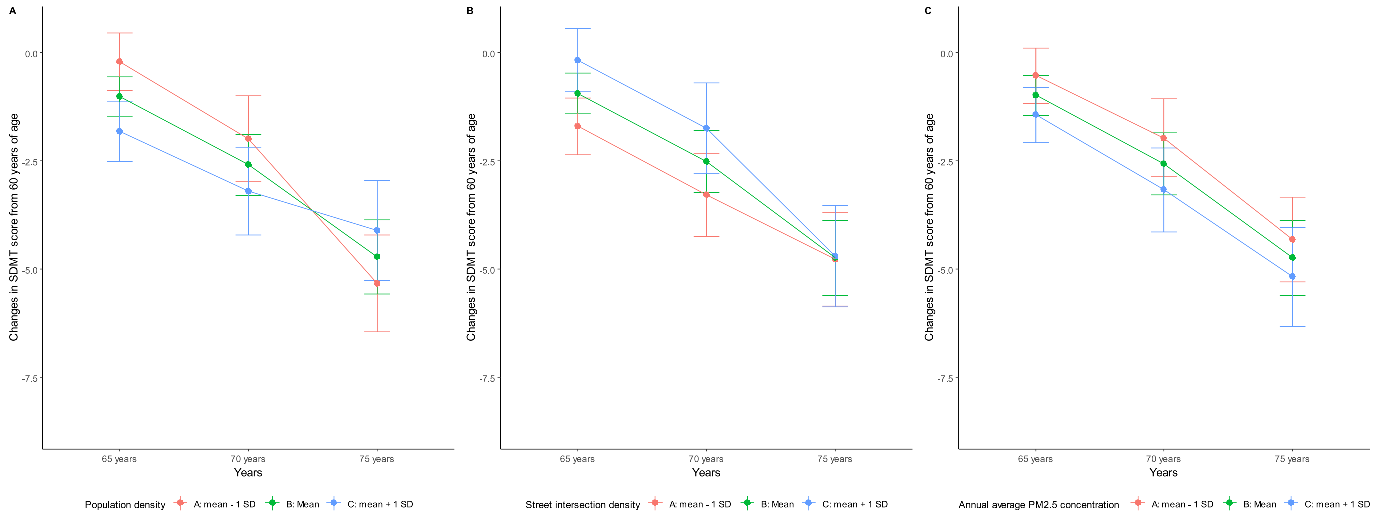

Fig. 4. Moderating effects of environmental attributes on changes in Symbol Digit Modalities Test (SDMT) scores from 60 years of age. Direct effect estimates for person-level average population density (panel A), street intersection density (panel B) and average annual concentrations of $PM_{2.5}$ (panel C).

Table 5
Total effects of neighbourhood environmental attributes on transitions to cognitive states.

Neighbourhood environmental attribute (person-level average)	No MCI/dementia to MCI/dementia	MCI to no MCI
	HR (95 % CI)	HR (95 % CI)
Population density (1000 persons/km^2)	0.62 (0.43, 0.90)	0.18 (0.06, 0.53)
Street intersection density (intersections/km^2)	1.00 (0.98, 1.02)	1.00 (0.96, 1.03)
Transit points (train stations and bus stops)	0.91 (0.88, 0.94)	0.88 (0.82, 0.92)
Commercial land (% within 1 km buffer)	0.93 (0.89, 0.97)	0.93 (0.86, 1.01)
Non-commercial land use mix (10 * unit)	0.84 (0.71, 0.99)	0.70 (0.58, 0.85)
Parkland (% within 1 km buffer)	0.98 (0.96, 0.99)	0.93 (0.93, 1.01)
Tree cover (% within 1 km buffer)	0.98 (0.96, 1.00)	1.01 (0.98, 1.05)
Blue space (presence within 1 km)	0.42 (0.21, 0.82)	0.29 (0.06, 1.35)
$PM_{2.5}$ (μg/m^3)	1.59 (0.77, 3.29)	0.43 (0.18, 1.01)
NO_2 (ppb)	2.13 (1.20, 3.78)	1.60 (0.97, 2.63)

Notes. MCI, mild cognitive impairment; HR, hazard ratio; CI, confidence interval; $PM_{2.5}$, particulate matter with a diameter of 2.5 μm (micrometres) or smaller; NO_2, nitrogen dioxide; ppb, parts per billion. Estimates adjusted for confounders. Inverse probability weights were used to address selection bias.

with better cognitive health outcomes. The opposite was observed for ambient air pollution (Table 6). We discuss our findings by categories of environmental attributes starting from the most proximal to cognitive health – namely, ambient air pollution (Fig. 1).

4.1. Ambient air pollution

Collectively, the two indicators of ambient air pollution examined in this study were negatively associated with all measures of cognitive health (Table 6). According to animal studies, $PM_{2.5}$ can have direct adverse effects on cognition by reaching the brain via circulation or direct infiltration through the olfactory bulb, and indirect effects by harming cardiometabolic health (Kilian & Kitazawa, 2018; Livingston et al., 2020; Power et al., 2016). Exposure to NO_2 is also deemed to contribute to neurodegenerative processes via cardiometabolic health and other pathways linked to dementia pathogenesis (Kilian & Kitazawa, 2018; Power et al., 2016).

It is interesting that both $PM_{2.5}$ and NO_2 showed more consistent negative associations with cognitive function at the within-person level. Increases in concentrations rather than higher person-level average concentrations of air pollutants were more frequently associated with worse cognitive outcomes (Table 6). As noted earlier, within-person effects are not biased by person-level (time-invariant) confounders, such as residential self-selection or unmeasured socio-demographic factors (Allison, 2005). Consequently, they have more power to detect associations in the presence of person-level negative confounding (i.e., confounding that biases an association toward the null). For example, physically and socially active individuals may choose to live in vibrant neighbourhoods that provide better access to services (residential self-selection) but also higher levels of exposure to air pollutants from traffic and food outlets. In urban areas with relatively low levels of air pollution like in our study, leading an active lifestyle in a destination-rich, relatively more polluted environment may result in as good a cognitive health as leading a less active life in a destination-poor, less polluted environment. Yet, when accounting for individual differences in residential preferences and behaviours in longitudinal analyses, our study suggests that increases in air pollution result in worse cognitive health.

4.2. The natural environment

Overall, as hypothesised, the natural environment features examined in this study were predictive of better cognitive health (Table 6). Person-level average access to both parkland and blue spaces was associated with a lower risk of transition to MCI. These are novel findings given that no prior studies examined the effects of exposure to the natural environment on transitions to cognitive states.

The associations of natural environment indicators with continuous measures of cognitive function were not as compelling as those for indicators of ambient air pollution. Person-level average percentage of parkland in the residential buffer was associated with lower rather than higher scores on the verbal memory test (CVLT – immediate recall),

Table 6
Summary of findings by neighbourhood environmental attribute.

Environmental attribute	Findings suggestive of a beneficial effect on cognition	Findings suggestive of a harmful effect on cognition
Population density (PD)	↑ PD, ↓ likelihood of transition to MCI↑ PD, slower decline in SDMT score (processing speed) from 70 to 75 yearsIncrease in PD associated with increase in MMSE score (global cognition)	↑ PD, ↓ likelihood of reversal to no MCI↑ PD, steeper decline in SDMT score (processing speed) from 60 to 70 yearsIncrease in PD associated steeper decline in digit span backwards score (verbal working memory) *↑ PD, ↓ digit span backwards score (verbal working memory)* *Increase in PD associated with decrease in CVLT – immediate recall (verbal memory)*
Street intersection density (SID)	↑ SID, ↑ SDMT score (processing speed)↑ SID, ↑ MMSE score (global cognition)↑ SID, slower decline in SDMT score (processing speed) from 60 till 70 years of ageIncrease in SID associated with increase in SDMT score (processing speed) *↑ SID, slower decline in MMSE score (global cognition)* *Increase in SID associated with increase in digit span backwards (verbal working memory)*	↑ SID, steeper decline in SDMT score (processing speed) from 70 to 75 years
Transit points (TS)	↑ TS, ↓ likelihood of transition to MCI *↑ TS, slower decline in MMSE score (global cognition)* *Increase in number of TS, increase in MMSE score (global cognition)*	↑ TS, ↓ likelihood of reversal to no MCIIncrease in number of TS, decrease in digit span backwards (verbal working memory)
Commercial land (CL)	↑ CL, ↓ likelihood of transition to MCI↑ CL, ↑ MMSE score (global cognition)↑ CL, slower decline in MMSE score (global cognition) *Increase in CL associated with slower decline in digit span backwards score (verbal working memory)*	Increase in CL associated with steeper decline in MMSE score (global cognition)
Non-commercial land use mix (LUM)	↑ LUM, ↓ likelihood of transition to MCI↑ LUM, ↑ SDMT scores (processing speed)Increase in LUM associated with an increase in SDMT score (processing speed)Increase in LUM associated with an increase in MMSE score (global cognition)	↑ LUM, ↓ likelihood of reversal to no MCI
Parkland	↑ parkland, ↓ likelihood of transition to MCIIncrease in parkland associated with an increase in CVLT – immediate recall score (verbal memory)	↑ parkland, ↓ CVLT – immediate recall score (verbal memory)
Tree cover	↑ tree cover, ↑ CVLT – immediate recall scores (verbal memory) *↑ tree cover, ↑ MMSE scores (global cognition)*	
Blue space (BS)	↑ access to BS, ↓ likelihood of transition to MCI↑ access to BS, ↑ SDMT score (processing speed)	↑ access to BS, steeper decline in MMSE score (global cognition)
$PM_{2.5}$		↑ $PM_{2.5}$, steeper decline in digit span backwards score (verbal working memory) ↑ $PM_{2.5}$, steeper decline in SDMT score (processing speed) Increase in $PM_{2.5}$ associated with a decrease in digit span backwards score (verbal working memory) Increase in $PM_{2.5}$ associated with a steeper decline in digit span backwards score (verbal working memory) *Increase in $PM_{2.5}$ associated with a decrease in MMSE score (global cognition)*
NO_2		↑ NO_2, ↑ likelihood of transition to MCI Increase in NO_2 associated with a steeper decline in MMSE score (global cognition) Increase in NO_2 associated with a steeper decline in CVLT – immediate recall score (verbal memory) from 70 to 75 years *Increase in NO_2 associated with a decrease in SDMT score (processing speed)*

Notes. MCI, mild cognitive impairment; CVLT, California Verbal Learning Test; SDMT, Symbol Digit Modalities Test; MMSE, Mini Mental State Examination; $PM_{2.5}$, particulate matter with a diameter of 2.5 μm or smaller; NO_2, nitrogen dioxide; ↑, higher/better/more; ↓, lower/worse. In *italics*: effect not statistically significant after adjustment for other environmental attributes.

while increases in parkland and higher levels of tree cover were suggestive of a beneficial effect on verbal memory. No significant associations were found with processing speed (SDMT) or working memory (digit span backwards). Also, a positive association (total effect model) between tree cover and global cognition (MMSE) vanished after accounting for other natural environment features and air pollution (direct effect model).

Several factors might have contributed to more limited evidence for the beneficial effects of greenness on cognitive function than expected. The average and median percentage of parkland was relatively high (16 % to 18 %) compared to that reported in other studies. For example, a study conducted in Scotland reported a median percentage ranging from 7.0 % to 8.4 % (Cherrie et al., 2018) and another based in the U.S. reported an average of 4.9 % of park space within residential buffers (Besser et al., 2021). In our study, only 10–15 % of participants lived in areas with less than 8 % of parkland. If the effect of parkland availability on cognitive health is curvilinear (e.g., inverse-U shape; Wu et al., 2015), it is possible that most participants had enough parkland in their residential area to support cognitive health. Another issue pertains to the type of measure of greenness used. Percentage of parkland does not distinguish between different types of green spaces (e.g., open grass, woodland or impenetrable bushland) (Astell-Burt et al., 2020) and does not capture information on the quality of such spaces (e.g., maintenance, facilities or features). A few recent studies have suggested that woodland and tree canopy may be more relevant to older adults' cognitive health than overall greenness or access to parkland (Astell-Burt et al., 2020; Godina et al. 2023). In line with these findings, in the present study, tree canopy showed only beneficial associations with cognitive health, while this was not the case for percentage of parkland.

It is noteworthy that, in this study, the cross-sectional association of parkland with verbal memory was negative, while its longitudinal counterpart was positive. Likewise, the longitudinal evidence of a beneficial effect of greenness on older adults' cognitive health has been considerably more consistent than the evidence from cross-sectional studies (Besser et al., 2021b; Besser et al., 2020; Cerin et al., 2021; Cerin et al., 2023; Chan et al., 2023; Cherrie et al., 2018; de Keijzer et al., 2018; Zhu et al., 2019), which are prone to the negative confounding effects of residential self-selection. Individuals who choose to live in quiet neighbourhoods with a large proportion of green space may do so to enhance their mental well-being because they are more vulnerable to stress and mental disorders, which, in turn, are associated with worse cognitive health (Besser et al., 2021a; Livingston et al., 2020).

Finally, it is interesting that, in this study, indicators of greenness were mainly related to one cognitive domain – verbal memory. Memory tasks require the ability to sustain internally targeted attention (Kiyonaga & Egner, 2013). Because there is evidence that exposure to green spaces restores voluntary attention (Cassarino & Setti, 2015; de Keijzer et al., 2020), it is perhaps not surprising, especially in an environment with relatively low ambient air pollution, that our findings are suggestive of a beneficial effect on verbal memory than other cognitive domains that are less dependent on internal attention (processing speed and global cognition). In areas with higher levels of ambient air pollution, green spaces may exert a more pronounced beneficial effect on other cognitive domains by reducing pollution levels (Hu et al., 2023). The lack of an association between tree canopy and global cognition after adjustment for air pollutants observed in our study provides support for this pathway of influence.

While access to blue spaces was predictive of better cognitive outcomes based on clinical assessments, only two significant but contrasting associations were observed in relation to cognitive function (processing speed and global cognition), both of which were with the person-level average measure of access to blue spaces. The inconsistent findings hint at possible residential self-selection and other sources of bias (Besser et al., 2021a; White et al., 2021) and are in line with the few studies that examined the same topic (Cerin et al., 2022, Klompmaker et al., 2022; Wu & Jackson, 2021; Zijlema et al., 2019). As with green spaces, different types of water bodies may confer different benefits to cognitive health in different geographical contexts. For example, White and colleagues (White et al., 2021) examined associations of inland- and coastal-blue spaces with mental well-being and found that the effects varied by country. Although the mechanisms through which blue spaces influence cognitive health are thought to be similar to those of green spaces (e.g., stress reduction, opportunities for physical and social activities) (Cerin et al., 2024), the current evidence on the former is much sparser and conflicting, requiring further research.

4.3. The built environment

Most built environment attributes were associated with a lower risk of transitioning to MCI, but also a lower likelihood of reversal to no MCI. The first set of findings supports the hypothesis that dense, walkable environments benefit cognitive health in cognitively intact older adults by providing opportunities to engage in cognition-enhancing activities (e.g., incidental physical activity, social and cultural activities, environmental complexity) (Besser et al., 2017; Cerin et al., 2020a; Cerin et al., 2020b). With respect to the second set of findings, we need to consider that risk estimates were unadjusted for air pollution due to the low number of cases transitioning to the various cognitive states. Higher levels of environmental stressors present in dense, destination-rich neighbourhoods may reduce the likelihood of improvements in cognitive state, especially in those with more advanced neuropathology (Kulick et al., 2020). Moreover, higher environmental complexity and clutter may pose challenges to people with impaired cognition and deter them from engaging in activities in the community (Cassarino & Setti, 2015). Another possible reason for the observed findings is of statistical nature. Given the low number of participants with MCI/dementia and built environment attributes appearing protective of conversion to MCI, the number of MCI/dementia cases in high walkable environments might have been too low to provide sufficient variability in reversal outcomes.

The pattern of relationships of the built environment with cognitive function domains, which were also adjusted for air pollution and other environmental mediators, was more supportive of beneficial than detrimental effects (Table 6). This was especially the case for non-commercial land use mix, street intersection density and percentage of commercial land, which are indicators of destination accessibility as well as environmental complexity (Cassarino & Setti, 2015). Importantly, both person-level average and within-person exposures showed significant positive effects, suggesting that the associations cannot be purely attributed to residential self-selection (Besser et al., 2021a). In contrast to the natural environment, built environment indicators were more often positively related to global cognition (MMSE) and processing speed (SDMT) than memory, with which a number of negative associations emerged (Table 6). Complex, dynamic environments require external attentional focus and fast scanning of stimuli (Cassarino & Setti, 2015) which are at odds with memory tasks (Kiyonaga & Egner, 2013) and more in line with tasks requiring fast processing of visual information (e.g., SDMT). Also, living in more complex urban environments with opportunities for social engagement and other activities may help maintain or improve orientation to time and place as well as visuospatial and language skills, all of which are facets of global cognition (MMSE; Folstein et al., 1975).

4.4. Strengths and limitations

This study addressed several important research gaps in the field of environmental determinants of cognitive health in late life. It examined the cross-sectional as well longitudinal associations of key causally interrelated neighbourhood environmental attributes with several cognitive health outcomes, including transitions to clinically assessed cognitive states, which was made possible by the long follow-up time (12 years) and number of assessments (four time points). This is a major strength as past studies typically focussed on one or two domains of the neighbourhood environment (e.g., greenness and air pollution) and, consequently, did not account for key environmental confounders (e.g., access to destinations). Moreover, those that considered all categories of neighbourhood environmental features were cross-sectional. Another strength of our study is the utilisation of standardised clinical protocols in diagnosing MCI or dementia.

This study is not void of limitations. Firstly, we did not have building-level residential information for a large proportion of participants and, for a smaller proportion of them, we did not have full residential addresses for the first 3 waves. Although we used inverse probability weighting to account for selection bias, the possibility of residual bias cannot be discounted. In fact, no deaths were recorded during the 12-year follow-up period, indicating that the analytic sample was relatively healthy. Assuming that the neighbourhood environment is causally related to cognitive health, this might have resulted in attenuated environment-cognitive health associations. Individuals who might have died or dropped out from the study between Waves 1 and 4 due to dementia might have been particularly susceptible to the effects of the environmental exposures examined in this study.

We had environmental data for only two rather than four time points, and for a couple of neighbourhood attributes (tree cover and number of buses), we had a single value for the study period. This would have contributed to exposure misclassification yielding downward biased estimates of effects and the inability to clearly establish temporality. Data on land use, including parkland, were limited as they only included the dominant use within an administrative area. This might have attenuated the associations between land use based spatial indicators and cognitive outcomes as well as partly confounded the effects of the natural environment and air pollution with cognition (Cerin et al., 2021). Detail on the types and quality of green and blue spaces was also limited. Possible residual confounding of SES factors, which are difficult to partial out completely, may have resulted in somewhat biased estimates of associations. Moreover, clinical assessments of reversal from MCI to no MCI might have been in part due to measurement errors rather than improvements in cognition (Park & Han, 2015). Information on non-residential exposures and/or time typically spent in the neighbourhood was not available. Some participants might have spent a substantial proportion of their time outside the neighbourhood, resulting in a further attenuation of associations. Apart from adopting a comprehensive approach to the characterisation of the neighbourhood environment and explicitly modelling the interrelationships between its various components, future cohort studies on environmental determinants of cognitive health need to examine the contribution of exposures in residential as well as non-residential settings across geographical areas with substantial variability in environmental attributes (Cerin et al., 2020a; Cerin et al., 2020b). Finally, the effects of specific neighbourhood features on cognitive health may depend on socio-demographic characteristics, other health problems (Cerin et al., 2021) as well as other neighbourhood features (Cerin et al., 2023). Although these modifying factors were not examined in this study due to the extensive nature of the analyses undertaken, they will be the aim of future investigations.

5. Conclusions and practical implications

This study found consistent evidence suggestive of harmful effects of ambient air pollution on older adults' cognitive health in terms of clinically assessed cognitive impairment as well as levels, changes, and trajectories of various domains of cognitive function. We also found support for beneficial effects of the neighbourhood natural environment on maintenance of memory skills and normal cognition, although the evidence pertaining to blue spaces was less robust, requiring further investigation. Dense, complex, destination-rich urban environments appear to benefit cognitively intact individuals, especially with respect to global cognition and processing speed, while they may pose challenges to older adults with cognitive impairment and hinder the ability to sustain internal attention, which is important for memory. Future studies need to clarify the mechanisms underlying the observed associations and consider possible interactive effects of environmental attributes (Cerin et al., 2023). To support healthy ageing in place, there is a need for the creation of neighbourhoods with an optimal mix of environmental complexity, destinations for daily living and access to the natural environment (e.g., greenery and coastal waters) and, at the same time, implement strategies aimed at reducing ambient air pollution (e.g., the creation of pedestrianised areas or super blocks limiting motorised traffic).

CRediT authorship contribution statement

Ester Cerin: Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Maria V. Soloveva:** Writing – review & editing, Writing – original draft, Project administration. **Miguel A. Molina:** Writing – review & editing, Validation, Supervision, Software, Methodology, Investigation, Data curation, Conceptualization. **Ralf-Dieter Schroers:** Writing – review & editing, Software, Methodology, Investigation, Data curation. **Luke D. Knibbs:** Writing – review & editing, Methodology, Funding acquisition, Data curation. **Muhammad Akram:** Writing – review & editing, Validation, Software, Formal analysis. **Yu-Tzu Wu:** Writing – review & editing, Software, Funding acquisition, Conceptualization. **Suzanne Mavoa:** Writing – review & editing, Supervision, Funding acquisition. **Matthew Prina:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization. **Perminder S. Sachdev:** Writing – review & editing, Resources, Funding acquisition, Conceptualization. **Vibeke Sorensen Catts:** Writing – review & editing, Conceptualization. **Bin Jalaludin:** Writing – review & editing, Funding acquisition. **Govinda Poudel:** Writing – review & editing. **Mark Symmons:** Writing – review & editing. **Anthony Barnett:** Writing – review & editing, Supervision, Conceptualization. **Md Hamidul Huque:** Writing – review & editing. **Yvonne Leung:** Writing – review & editing. **Nicolas Cherbuin:** Writing – review & editing, Resources, Project administration. **Kaarin J. Anstey:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

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

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

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