Characteristics of Urban Neighbourhood Environments and Cognitive Age in Mid-Age and Older Adults

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Abstract

In this cross-sectional study, we examined the extent to which features of the neighbourhood natural, built, and socio-economic environments were related to cognitive age in adults (N = 3418, M_{age} = 61 years) in Australia. Machine learning estimated an individual's cognitive age from assessments of processing speed, verbal memory, premorbid intelligence. A 'cognitive age gap' was calculated by subtracting chronological age from predicted cognitive age and was used as a marker of cognitive age. Greater parkland availability and higher neighbourhood socio-economic status were associated with a lower cognitive age gap score in confounder- and mediator-adjusted regression models. Cross-sectional design is a limitation. Living in affluent neighbourhoods with access to parks maybe beneficial for cognitive health, although selection mechanisms may contribute to the findings.

Keywords

Cognitive age; Parkland availability; Neighbourhood socio-economic status; Machine learning; Urban environments.

Highlights

- Greater parkland availability predicts younger cognitive age in older adults.
- Older adults from socially advantaged neighbourhoods have younger cognitive age.
- Exposure to greenspace can be a population-level approach to preserve cognition.
- Cognitive age gap can be a promising marker of cognitive health.

1. Introduction

With population ageing, the global number of people aged 65+ years are projected to grow to ~ 1.5 billion in 2050 (World Health Organisation, 2022), resulting in increased government expenditure and demand for health services, diminished labour force participation, and increased rates of age-dependent and neurogenerative disorders (Friendship, 2021). Progressive decline in cognitive function is a hallmark of normal ageing, and age-related cognitive changes are associated with an increased risk of mortality (Duan et al., 2020), disability (Barberger-Gateau & Fabrigoule, 1997), loss of independence (Domenech-Cebrían et al., 2019), and poor quality of life (Bárrios et al., 2013). Long-term population-level strategies that maintain and promote cognitive health in mid-age and older adults are, thus, needed. One proposed strategy is the creation of activity-friendly community environments for ageing populations (Cerin et al., 2017; Van Cauwenberg et al., 2018).

In accordance with the ecological model of cognitive health (Cerin, 2019, please see Fig. 1), neighbourhood natural (e.g., parks, blue spaces) and built environments (e.g., dwelling density, retail and shops) influence cognitive health *directly* and *indirectly.* A simplified version of the ecological model, which has been adapted to the present study, is presented in Fig. 2.

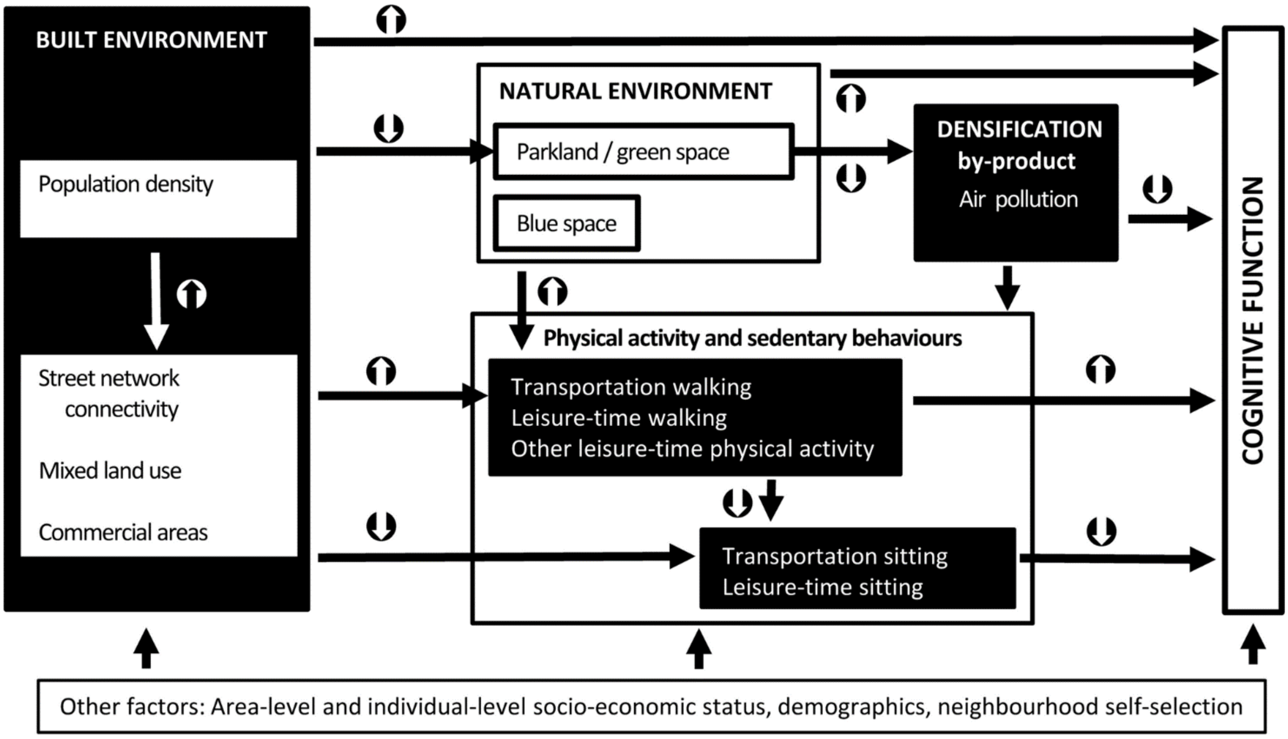

Fig.1. A simplified ecological model of how different neighbourhood attributes are related to cognitive health (Cerin, 2019).

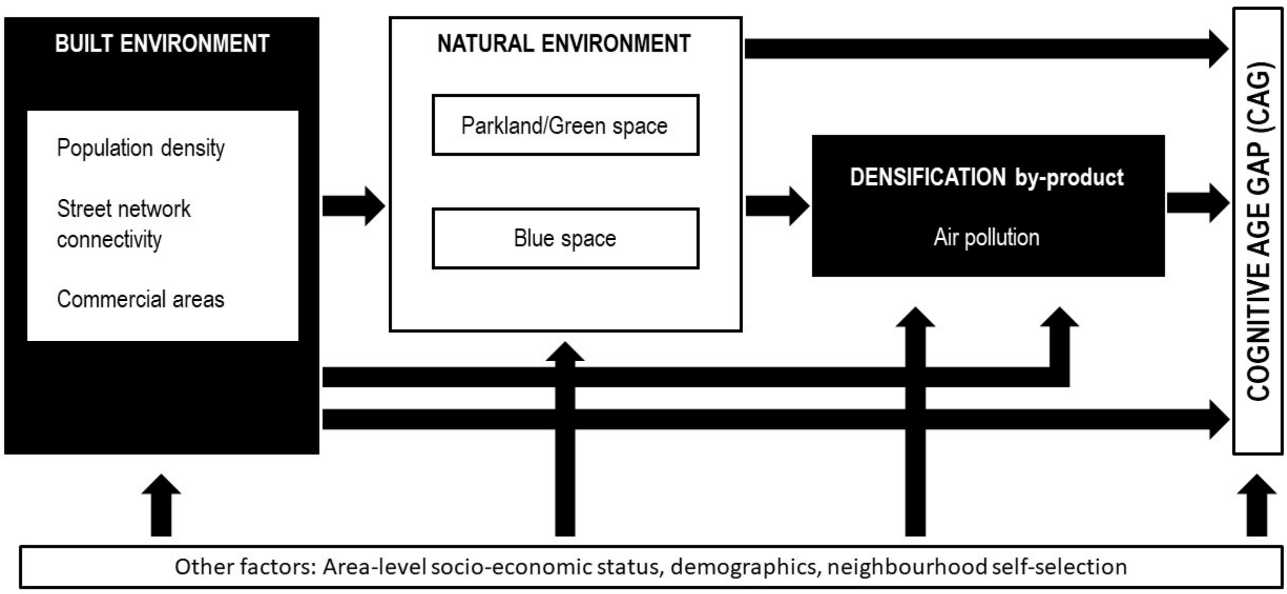

Fig. 2. A simplified ecological model of neighbourhood environmental influences on cognitive age gap.

The *direct* effect of the neighbourhood environment on cognition pertains to the exposure of residents to harmful factors, such as ambient air pollution (Cerin et al., 2021; Tham et al., 2022) and to relaxing and aesthetically-pleasing environments (e.g., greenery, natural sights) (Cherrie et al., 2018; de Keijzer et al., 2018) and/or complex visual and spatial layouts that require cognitive effort to navigate the neighbourhood (Cassarino & Setti, 2015; Watts et al., 2015). For example, air pollutants reach the brain via the olfactory nerve in the circulatory system, leading to high levels of oxidative stress, neuroinflammation and microglial activation – the processes that impair cognitive function and are associated with an increased risk of neurodegeneration (Chen et al., 2015; Elder et al., 2006; Jankowska-Kieltyka et al., 2021). Further, beneficial effects of greenery on cognitive function might be accrued from psychological restoration, as after spending time in parks, individuals have been found to improve concentration and recover from stress and mental fatigue, which, in turn, influence cognitive function (Kaplan, 1995).

The neighbourhood environment can also impact on cognitive health *indirectly* via its effects on cognition-enhancing lifestyle behaviours. For example, by providing access to natural environments (e.g., parks and blue spaces), residents are more likely to engage in leisure-time physical activity and social activities that are known to positively influence cognition (Cerin et al., 2021; Sylvers et al., 2022). As depicted in Fig. 1, dense, destination-rich communities with good access to public transport encourage mid-age and older adults to walk, and engagement in physical activity is known to lead to improvements in memory performance and mental alertness, as well as reduced risk of dementia (Rachele et al., 2019; Roe et al., 2020; Sylvers et al., 2022). Socio-economically advantaged neighbourhoods tend to be associated with better cognitive health in older adults (Besser et al., 2017; Clarke et al., 2012) and reduced risks of dementia (Pase et al., 2022) compared to neighbourhoods with lower socio-economic status, possibly because they provide many opportunities for individuals to engage in physical, cognitive and social activities (Settels & Leist, 2021), and these are the well-known predictors of higher cognitive reserve in non-clinical populations (Barulli & Stern, 2013; Soloveva et al., 2018; Song et al., 2022). There is limited and inconsistent research in respect to how features of the neighbourhood natural, built, and socio-economic environments are *conjointly* related to cognitive function in multiple-exposure models in mid-age and older adults (Cerin, 2019; Giles-Corti et al., 2022), with studies focusing on a single and/or a limited range of neighbourhood characteristics that relate to cognition. As an example – access to various services in the neighbourhood can be simultaneously beneficial (by promoting an active lifestyle) and detrimental to cognitive health (by exposing residents to air pollution and reducing exposure to greenery). Therefore, the omission of key neighbourhood characteristics that act as confounding or mediating variables is likely to result in a biased evaluation of environmental correlates of cognitive health (Cerin, 2019). Hence, there is a need to account for all key environmental attributes in the analysis. Further, research on whether certain environmental features are related to individual risk of cognitive deterioration is scarce and this is particularly relevant because trajectories of cognitive decline vary across adults, with some experiencing dramatic cognitive impairment relatively early in middle-late adulthood and others exhibiting only subtle cognitive changes in late life (Cloutier et al., 2015; Rocca et al., 2011). Thus, it is important to adopt a measure that can be used to adequately capture an individual's overall cognitive health, as well as to predict an individual's risk of cognitive decline.

The cognitive age gap (CAG), known as the difference between an individual's age predicted using scores in cognitive tests (predicted cognitive age) and their chronological age, has recently emerged as a potential marker of the cognitive ageing process (Anatürk et al., 2021; de Lange et al., 2022). Specifically, negative and/or small CAG values indicate a younger, cognitively healthier brain, whereas positive and/or large CAG values are suggestive of accelerated ageing. Predicted cognitive age is estimated using machine learning techniques, an analytical approach that builds regression models based on scores from standardised cognitive tests and is believed that it offers greater predictive accuracy in comparison to traditional statistical regression models (Park et al., 2020; Tzang et al., 2020).

To our knowledge, no previous studies have examined key categories of neighbourhood environmental correlates of CAG, as recommended by ecological models of neighbourhood features and cognitive health in ageing populations (Cerin, 2019; Finlay et al., 2022). This study aimed to estimate the conjoint total and direct cross-sectional associations of features of the neighbourhood natural, built, and socio-economic environment with CAG in a large sample of mid-age and older adults in Australia (n = 3418). We used a gradient boosting machine to predict an individual’s cognitive age based on scores from standardised cognitive assessments of processing speed, verbal memory, and premorbid intelligence. Processing speed and verbal memory are facets of cognition that deteriorate early in the ageing process (Harada et al., 2013), while premorbid intelligence, is a well-known proxy of cognitive reserve (Stern, 2009), and has been shown to relate to younger cognitive age (i.e., smaller CAG values) (Anatürk et al., 2021). We hypothesised that residents of more socially advantaged and dense neighbourhoods, with lower exposure to air pollution and greater access to the natural environment and various destinations, would be cognitively younger than their counterparts.

2. Methods

2.1. Participants

We used cross-sectional data from the third wave of the Australian Diabetes, Obesity and Lifestyle Study (AusDiab), a population-based, longitudinal survey aimed to examine the prevalence, incidence, and determinants of diabetes in Australian adults. Data was collected during 2011-2012 (Tanamas et al., 2013). Sampling procedure and power calculations are described elsewhere (Dunstan et al., 2002). The study was approved by the Alfred Hospital Ethics Committee, Melbourne, Australia. Details about AusDiab data collection procedures are provided elsewhere (Abe et al., 2021; Anstey et al., 2015; Tanamas et al., 2013). Of note, AusDiab collected cognitive function data only in Wave 3.

Participants were eligible to partake in AusDiab if they were: (1) aged 25 years and older; and (2) resided at their addresses for at least six months prior to the survey. A total of 473 participants were excluded from the analyses because they did not reside in urban areas, defined as towns and cities of 10,000 people or more. The final analytical sample consisted of 3418 participants (Table 1).

Table 1. Sample characteristics (n = 3418).

Characteristics	Statistic	Characteristics	Statistic
Socio-demographic characteristics		**Environmental characteristics (1km radius street-network buffers), mean (*SD*)**	
Age, years, mean (*SD*)	61.3 ± 11.4	Population density (persons/hectare)	17.5 (10.3)
Educational attainment, No. (%)		Street intersection density (intersections/km2)	62.0 ± 32.4
Up to secondary	1135 (33.5)	Percentage of commercial land use (% of area)	2.5 ± 6.1
Trade, technician certificate	979 (28.9)	Percentage of parkland (% of area)	11.6 ± 12.5
Associate diploma & equivalent	505 (14.9)	Percentage of blue space (% of area)	0.2 ± 2.0
Bachelor degree, post-graduate diploma	774 (22.8)	Annual average NO_2 (ppb)	5.5 ± 2.0
Missing data, No. (%)	25 (0.7)	Annual average $PM_{2.5}$ (µg/m3)	6.3 ± 1.7
Living arrangements, No. (%)		**Cognitive function**	
Couple without children	1642 (49.6)	Cognitive age gap, mean (*SD*)	-0.5 ± 8.5
Couple with children	896 (27)	Missing data, No. (%)	535 (15.6)
Other	775 (23.4)		
Missing data, No. (%)	105 (3.1)		
Residential self-selection - access to destinations, *M* ± *SD*	3.1 ± 1.4		
Missing data, No. (%)	313 (9.2)		
Residential self-selection - recreational facilities, *M* ± *SD*	3.1±1.5		
Missing data, No. (%)	313 (9.2)		
Sex, No. (%)			
Female	1901 (55.6)		
Male	1517 (44.4)		

Area-level IRSAD, *M* ± *SD*	6.4 ± 2.7
Ethnicity, No. (%)	
English-speaking background	3050 (89.2)
Non-English-speaking background	368 (10.8)
Household income, No. (%)	
Up to $49,999	1128 (34.1)
$50,000- $99,000	879 (26.6)
$100,000 and over	985 (29.8)
Does not know or refusal	316 (9.6)
Missing data, %	110 (3.2)

Abbreviations. *M*, mean; S*D*, standard deviation; IRSAD, Index of Relative Socioeconomic Advantage and Disadvantage where higher IRSAD scores indicate higher area-level socioeconomic status; NO_2, nitrogen dioxide; $PM_{2.5}$ particulate matter <2.5 μm; environmental characteristics have no missing data.

2.2. Measures

2.2.1. Environmental measures

Environmental exposure data consisted of aspects of the neighbourhood natural, built and socio-economic environment, and air pollution. Neighbourhood was defined as an area within a 1-km street-network distance from a participant's residential address (Barnett et al., 2018; Cerin et al., 2020). Natural features included percentage of parkland and blue space (within a neighbourhood). Data on these features were respectively derived from the 2011 Australian Bureau of Statistics (ABS) Mesh Block data (ABS, 2011) and Geoscience Australia data on surface water features (Crossman, 2015). Built environmental attributes were population density (persons/ha) and percentage of commercial land use (retail, office space, excluding industrial use) derived from the 2011 ABS Mesh Block data, and street intersection density (intersections/km^2) derived from the PSMA Australia's 2012 Transport & Topography dataset (PSMA, 2012). The ABS Mesh Block data from the 2011 Census provided information on the Index of Relative Socio-Economic Advantage and Disadvantage (IRSAD) at the SA1 (Statistical Area 1) level for residential neighbourhoods. Air pollution exposures were annual average concentrations of nitrogen dioxide (NO_2, units: ppb) and fine particulate matter <2.5 µm in aerodynamic diameter ($PM_{2.5}$, units: µg/m^3). Exposures to both air pollutants were estimated at each residential address using satellite-based land-use regression (LUR) models (Knibbs et al., 2018; Knibbs et al., 2016; Knibbs et al., 2014). Further details on the data sources, measures, validations and justifications for including them in this study are provided elsewhere (Anstey et al., 2015; Bagheri et al., 2021; Cerin et al., 2021; Knibbs et al., 2014). Socio-demographic and neighbourhood variables are described in Appendix A.

2.2.2. Cognitive measures

Symbol Digit Modalities Test (SDMT; Smith, 1982) was used to assess processing speed, referring to how fast an individual processes information on a cognitive task (Harada et al., 2013). Participants were asked to match symbols to their corresponding numbers in 90 seconds and were instructed to do so as fast as possible. The outcome measure was the total number of correct responses given by a participant (score range 0-60).

The world list from the California Verbal Learning Test (CVLT; Delis et al., 1987) was used to assess memory. Participants were shown a list of 16 common shopping list items five times (List A) and after the first trial were asked to repeat as many words as possible (immediate recall). After a delay of 20 minutes, 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.

Spot the Word Test (STWT; Baddeley et al., 1993) is a lexical decision task that was used to assess premorbid intelligence. Participants were presented with 60 pairs of items comprising one real word and one non-word and they were required to identify the real word by underlining the item in each pair. One point was scored for every correct word (score range 0-60).

2.3. Statistical analyses

2.3.1. Determining the Cognitive Age Gap (CAG)

The caret package version 6.0-92 (Kuhn et al., 2008) for R version 4.2.0 (https://www.r-project.org/) was used to develop a machine learning regression model (using Gradient Boosting Machine (GBM)) to predict age (model output) using scores from three cognitive assessments (model inputs). From the original dataset of 4141 participants, we excluded those (n = 723) that were used to train the GBM regression model of predicted cognitive age, resulting in a final analytical sample of 3418. We randomly selected 20% of cases (n = 723) from those with complete cognitive assessment data (n = 3606 from N = 4141) to build a machine learning model of cognitive age. Ten-fold cross-validation with five repetitions was used during training. The trained GBM regression model was used to predict the cognitive age of individuals in the remaining 80% of the dataset comprising 2883 individuals. Lastly, CAG was computed for each of these individuals by subtracting their chronological age from predicted cognitive age and was used for further statistical analyses.

2.3.2. Main analyses: associations between neighbourhood environmental measures and CAG

From the original dataset of 4141, nearly 16% of cases had missing data on at least one variable, 11% on at least two variables, and 3.5% on more than 3 variables. Under a missing at random assumption (Table S1, Figure S1 in Appendix B and Appendix C), twenty imputed datasets were, therefore, created for the multivariable regression analyses following recommended procedures (Van Buuren & Groothuis-Oudshoorn, 2011). Generalised additive mixed models (GAMMs; package 'much' version 1.8-40 in R) (Wood, 2017) with random intercepts at the SA1 level were used to estimate cross-sectional total and direct effects of environmental attributes on CAG to allow for possible curvilinear effects (Table S2 in Appendix D). Here, by total and direct effects we refer, respectively, to associations between specific environmental attributes and CAG unadjusted and adjusted for other environmental attributes deemed to mediate the associations. Directed acyclic graphs (DAGs) informed the selection of a minimal sufficient set of confounders and/or covariates (here defined as variables associated with the outcome) for the statistical analyses (Tables S3-S4, Figure S2 in Appendix E, Appendix F and Appendix G). Gaussian variance and identity link functions were used in GAMMs because CAG was approximately normally distributed. Potential multicollinearity was assessed by computing the Variance Inflation Factor (VIF) for each variable included in the GAMMs. All VIFs were smaller than 3, indicating no collinearity issues (Sheather, 2009). Multivariable regression analyses were also conducted on non-imputed data (Tables S5-S6 in Appendix H and Appendix I).

3. Results

3.1. Demographics characteristics

The average age of the sample was 61 years (SD = 11, range: 34-97 years) (Table 1). Nearly 90% of participants were of English-speaking background. Most were female and living with a partner but without children. There was substantial variability in educational attainment, household income and several neighbourhood environmental attributes. The average percentage of residential buffer area devoted to non-commercial land use (2.5%) and blue space (0.2%) was lower than that devoted to parks (11.6%). The annual average concentrations of air pollutants were relatively low, with NO_2 and $PM_{2.5}$ reaching 5.5 ppb and 6.3 µg/m^3, respectively. An overview of the complete data (n = 2883) is provided in Table S7 in Appendix J.

3.2. Determining CAG

The GBM model developed using the training dataset (n = 723, age range of 36-92, M_{age} = 60.1 and SD_{age} = 11.1) was successfully applied to estimate cognitive age of each participant from the testing dataset (n = 2883, age range of 35-97, M_{age} = 60.7, SD_{age} = 11.1) yielding a linear regression model with satisfactory performance in predicting cognitive age

(Table S8, Figure S3 in Appendix K and Appendix L). CAG was, on average, -0.5 years and ranged from -31.3 and 29.4 years.

Furthermore, to address the utility of machine learning, we have conducted a sensitivity analysis by testing whether a ML-based CAG as the outcome measure in this study is superior to a linear regression-based CAG. We have used individual standardised cognitive test scores to predict chronological age, which is referred to as predicted cognitive age. We found that models based on CAG as the outcome performed on all indicators equally or slightly superior in predicting chronological age from cognitive tests compared to traditional methodology (please see Tables S9-S10 in Appendix M and N).

3.3. Neighbourhood environmental correlates of CAG

The total and direct associations of neighbourhood environmental attributes with CAG are reported in Table 2 and Table 3. The linear model was a better fitting model for examining the relationships between aspects of natural, built and socio-economic neighbourhood environments with CAG (please see Table S2 in Appendix D). In the total-effect models, higher percentage of parkland in a 1 km residential buffer and higher area-level socio-economic status were associated with smaller CAG scores, indicating a cognitively younger brain in mid-age and older adults. Likewise, parkland availability and neighbourhood socio-economic status showed positive direct effects on CAG in mid-age and older adults. We observed the strongest evidence for the parkland-CAG association (p = .004). No other statistically significant associations were observed.

Table 2. Total effects of environmental attributes on cognitive age gap.

Environmental Attribute	***b* (95% CI)**	***p* value**
Population density (persons/hectare)	-0.005 (-0.025, 0.015)	.60
Street intersection density (intersections/km^2)	0.004 (-0.003, 0.011)	.26
Percentage of commercial land use (% area in residential buffer)	0.017 (-0.015, 0.049)	.29

Percentage of parkland (% of area in residential buffer)	-0.023 (-0.039, -0.007)	**.004**
Percentage of blue space (% of area in residential buffer)	-0.028 (-0.119, 0.064)	.56
Area-level IRSAD	-0.096 (-0.177, -0.014)	**.02**
Annual average NO_2 exposure (ppb)	-0.031 (-0.160, 0.098)	.64
Annual average $PM_{2.5}$ exposure (µg/m^3)	-0.046 (-0.172, 0.080)	.47

Abbreviations. *b*, regression coefficient; CI, confidence intervals.
Effects in bold are statistically significant at a probability level of 0.05.

Table 3. Direct effects of environmental attributes on cognitive age gap

Environmental Attribute	*b* (95% CI)	*p* value
Population density (persons/hectare)	-0.005 (-0.035, 0.024)	.71
Street intersection density (intersections/km^2)	0.001 (-0.007, 0.008)	.86
Percentage of commercial land use (% area in residential buffer)	0.017 (-0.016, 0.049)	.31
Percentage of parkland (% of area in residential buffer)	-0.020 (-0.036, -0.004)	**.01**
Percentage of blue space (% of area in residential buffer)	-0.028 (-0.120, 0.063)	.54
Area-level IRSAD	-0.093 (-0.177, -0.009)	**.03**
Annual average NO_2 exposure (ppb)	-0.031 (-0.160, 0.098)	.64
Annual average $PM_{2.5}$ exposure (µg/m3)	-0.046 (-0.172, 0.080)	.47

Notes. *b*, regression coefficient; CI, confidence intervals.
Effects in bold are statistically significant at a probability level of 0.05.

4. Discussion

As hypothesised, we found that residents living in neighbourhoods with higher socio-economic status and with greater parkland availability were cognitively younger than their counterparts. The strength of the relationships between parkland availability, neighbourhood socio-economic status and CAG is similar to those found in studies of environmental correlates of health-related behaviours (Sallis et al., 2020). Contrary to our expectations, built environmental indicators and air pollution were not significantly associated with CAG.

Our study is the first to illustrate that higher percentage of parkland within a 1 km residential buffer was associated with younger cognitive age, as evidenced by smaller CAG scores. This novel finding is consistent with cross-sectional (Cerin et al., 2021) and longitudinal studies (Besser et al., 2021a; de Keijzer et al., 2018; Jimenez et al., 2022) showing associations of greater availability of local greenness with better cognitive function in older adults, and with lower odds of neurodegenerative conditions (Rodriguez-Loureiro et al., 2022). Importantly, the significant effect was observed in both the total- and direct-effect regression models, and after adjusting for known confounders of neighbourhood-cognition associations (e.g., neighbourhood self-selection, ethnicity, household income), highlighting that, in urban settings, parkland availability may play an important role in promoting cognitive health.

Furthermore, no significant association was observed between availability of blue space and CAG, which we believe is partly due to only ~4.5% (n = 186) of adults having access to blue space within their 1 km residential areas and, among these participants, over half having less than 2.25% of their neighbourhood covered by blue space. In support, the authors previously showed (McDougall et al., 2021) that mid-age and older adults (< 65 years) were 3.5% less likely to be prescribed antidepressant medication when exposed to a high freshwater blue space coverage (>3%); however, no positive effect on medication prescriptions was observed in residents living in a neighbourhood with no and/or limited availability of blue space (~ 0-0.25%), suggesting that the effects of exposure to blue spaces on CAG could depend upon on the amount of neighbourhood area that is devoted to natural environments. Further research is needed to establish whether there is a minimum percentage of parkland and/or blue space that is required to positively affect cognitive age in mid-age and older adults.

No significant associations were found between population density, street intersection density, commercial land use and CAG; however, past studies have shown that land use mix (Chan et al., 2022; Wu et al., 2015), access to local amenities (post office, libraries) and recreational sites (Clarke et al., 2015; Finlay et al., 2021), population density (Cerin et al., 2021; Saenz et al., 2018), public transport accessibility (Chan et al., 2022; Clarke et al., 2012), neighbourhood walking destination density (Besser et al., 2021b) and street intersection density (Watts et al., 2015) were associated with better cognitive function in older adults. A possible explanation for the finding might be that the built environment measures used in this study might have been too crude, failing to provide sufficiently detailed information on relevant destination types that support cognition-enhancing activities (Cerin et al., 2021; Poudel et al., 2022). Furthermore, the selected built environment features might have been too distal to observe significant associations between them and CAG. Mediation analyses focusing on the potential mechanisms explaining the nexus between the built environment and CAG, such as the type and frequency of physical activity and/or social contacts, might have yielded positive indirect effects (Cerin et al., 2022; Cerin et al., 2021; Jimenez et al., 2022). For example, the positive associations of population density with memory and processing speed performance in mid-age and older adults were in part explained by transportation walking (Cerin et al., 2021). Densely populated neighbourhoods with good access to public transport may encourage older adults to walk, and engagement in physical activity is associated with better cognitive health (Sylvers et al., 2022). Lastly, the examined built environment characteristics may only relate to specific cognitive functions (e.g., memory, alertness, inhibition) (Besser et al., 2021b), as opposed to an individual's overall cognitive ageing. These issues need to be clarified in future studies.

We found that higher neighbourhood socio-economic status, as indicated by higher IRSAD scores, was associated with younger cognitive age in mid-aged and older adults. This finding is in line with other studies, showing that affluent neighbourhoods relate to better cognitive health (Besser et al., 2017; Shih et al., 2011) and are associated with lower risks of age-dependent conditions (Pase et al., 2022). One of the underlying mechanisms that explains the association is that residents who live in affluent neighbourhoods are more likely to benefit from physical and leisure activities, social engagement, and cognitive stimulation (Besser et al., 2017; Sisco & Marsiske, 2012). Ihle and colleagues (2022) found that approximately 42.5% of the negative relationship between neighbourhood socio-economic status and older adults' rate of cognitive decline over a 6-year period was mediated by more frequent engagement in leisure activities, supporting the notion that neighbourhoods affect cognitive processes through increasing opportunities for a cognitively-enhancing lifestyle. Thus, neighbourhood socio-economic status is an important determinant of cognitive health and is supported by our finding that higher IRSAD predicts smaller CAG scores in mid-age and older adults.

Contrary to our hypothesis, annual average concentrations of $PM_{2.5}$ and NO_2 were not significantly associated with CAG in mid-age and older adults. While unexpected, these findings may be due to levels of air pollutants in our study possibly being too low to affect cognitive ageing, with mean NO_2 and $PM_{2.5}$ being 5.5 ppb and 6.3 μg/m^3, respectively. Significantly higher concentrations of air pollutants were observed in other countries. For example, some studies have reported values ranging from 10.54 to 12.6 μg/m^3 for $PM_{2.5}$ and 10.43 to 21.5 ppb for NO_2 in the U.S (Christensen et al., 2022; Wang et al., 2021), where worsened cognitive performance was observed among those living in more polluted areas.

4.1. Strengths and Limitations

This study has several strengths, such as utilising a large dataset (N = 3418) of Australian adults, with good geographical coverage and sample diversity. Unlike previous studies, we used a quantifiable and promising indicator (CAG) of normal cognitive ageing, estimated using supervised machine learning, to disentangle the conjoint linear and curvilinear effects of characteristics of the neighbourhood natural, built, and socio-economic environment in conjunction with ambient air pollution on cognitive age. Importantly, machine learning demonstrated equally or slightly superior predictive accuracy in predicting CAG over traditional methodology in a full and in a sub-sample of individuals aged 50+ years, which can be indicative of cognitive ageing (Appendix M and N). Though it is also important to note that machine learning would have demonstrated far greater superiority in comparison to traditional statistical regression models if a more comprehensive neurocognitive battery was used in predicting cognitive age.

Further, better performing individuals may be more likely to move to affluent neighbourhoods, as they may have higher education and occupation, or because they seek to have facilities within walking distance from home, and good access to physical activity infrastructure and health services (Besser et al., 2021b). We addressed the issue of reverse causality arising from neighbourhood self-selection (choosing to live in areas that support their lifestyle) by adjusting for this factor (captured by a neighbourhood self-selection questionnaire) in the regression models. We carefully considered any plausible associations among many other factors in the form of DAGs (Figure S2 in Appendix G).

Limitations include the cross-sectional nature of the study and the use of coarse measures of destination accessibility, which could have limited our ability to adequately examine the associations between urban environments and CAG and estimate causal effects. For example, an early life exposure to parkland and/or greater accumulation of parkland availability over the individual's life course could have contributed to younger cognitive age in adults (Clarke et al., 2014). Moreover, in our study, we cannot distinguish cognitive ageing from individual differences in cognitive performance at baseline (prior to declines due to ageing), as the data we used were cross-sectional. Another limitation is that we did not consider the potential variability of exposure to air pollution, as some participants could have experienced more days in which the air quality was dangerous to cognitive health. Lastly, our prediction of cognitive age may have been improved with a larger training dataset. Future research should address these limitations by conducting longitudinal studies to capture the trajectory of CAG changes across time, as there are different time windows of susceptibility to environmental exposures, and by more accurately characterising urban environments to delineate the impact of urbanicity on CAG. Future studies should also look into the role of relevant mediators, such as physical/social activities, to explain the complex relationships between the neighbourhood environment and CAG, and to advance our understanding of the relationship between air pollution and CAG. Future work is critical to improve the potential methodological and/or theoretical limitations of available age-prediction models. Lastly, we did not include a measure of overall brain health, and this is relevant, as positive associations between brain processes and cognitive performance were observed in past studies (Boyle et al., 2021; Chen et al., 2022).

4.2. Conclusions

We have shown that mid-age and older adults living in neighbourhoods with a higher socio-economic status and greater parkland availability are cognitively younger than their counterparts, as evidenced by smaller CAG values. Importantly, by examining CAG, it is possible to assess whether an individual's cognitive health is declining more quickly or more slowly than is typical for healthy individuals of the same chronological age, thereby, enabling early intervention. Furthermore, our results suggest urban environments that support a physically- and socially-active lifestyle may be beneficial for cognitive health. Specifically, green space exposure can be a feasible population-level approach to preserve cognitive health in ageing populations. There is a need to address the potential methodological and/or theoretical limitations of age-prediction models. Future longitudinal studies are needed to understand how urban built environmental attributes are related to the trajectory of CAG in mid-age and older adults and investigate causal relations among the variables of interest.

Conflict of Interest Disclosures

The authors declare they have no conflict of interest.

Institutional Review Board Statement

The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Alfred Hospital Ethics Committee, Melbourne, Australia (ref. no 39/11; 2 March 2011).

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

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The funders had no role in study design, data analysis, interpretation of the results, the decision to publish, or preparation of the manuscript.

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Data Availability Statement

Data that support the findings of this study are available on request under a license agreement. Written applications can be made to the AusDiab Steering Committee (Dianna.Magliano@baker.edu.au).

References

Abe, T., Carver, A., & Sugiyama, T. (2021). Associations of neighborhood built and social environments with frailty among mid-to-older aged Australian adults. *Geriatrics & Gerontology International*, *21*(10), 893-899. https://doi.org/10.1111/ggi.14253

ABS. Census of population and housing: mesh block counts, 2011 (cat. no. 2074). Canberra: Australian Bureau of Statistics; 2011.

Anaturk, M., Kaufmann, T., Cole, J. H., Suri, S., Griffanti, L., Zsoldos, E., Filippini, N., Singh-Manoux, A., Kivimäki, M., Westlye, L. T., Ebmeier, K. P., & de Lange, A.-M. G. (2021). Prediction of brain age and cognitive age: Quantifying brain and cognitive maintenance in aging. *Human Brain Mapping*, *42*(6), 1626-1640. https://doi.org/https://doi.org/10.1002/hbm.25316

Anstey, K. J., Sargent-Cox, K., Eramudugolla, R., Magliano, D. J., & Shaw, J. E. (2015). Association of cognitive function with glucose tolerance and trajectories of glucose tolerance over 12 years in the AusDiab study. *Alzheimer's Research & Therapy*, *7*(1), 48. https://doi.org/10.1186/s13195-015-0131-4

Baddeley, A., Emslie, H., & Nimmo-Smith, I. (1993). The Spot-the-Word test: A robust estimate of verbal intelligence based on lexical decision. *British Journal of Clinical Psychology*, *32*(1), 55-65. https://doi.org/10.1111/j.2044-8260.1993.tb01027.x

Bagheri, N., Mavoa, S., Tabatabaei-Jafari, H., Knibbs, L. D., Coffee, N. T., Salvador-Carulla, L., Anstey, K. J. (2021). The Impact of Built and Social Environmental Characteristics on Diagnosed and Estimated Future Risk of Dementia. *Journal of Alzheimer's Disease*, *84*(2), 621-632. https://doi.org/10.3233/JAD-210208. PMID: 34569946.

Barberger-Gateau, P., & Fabrigoule, C. (1997). Disability and cognitive impairment in the elderly. *Disability and Rehabilitation*, *19*(5), 175-193. https://doi.org/10.3109/09638289709166525

Barnett, A., Zhang, C. J. P., Johnston, J. M., & Cerin, E. (2018). Relationships between the neighborhood environment and depression in older adults: a systematic review and meta-analysis. *International Psychogeriatrics*, *30*(8), 1153-1176. https://doi.org/10.1017/S104161021700271X

Bárrios, H., Narciso, S., Guerreiro, M., Maroco, J., Logsdon, R., & de Mendonça, A. (2013). Quality of life in patients with mild cognitive impairment. *Aging & Mental Health*, *17*(3), 287-292. https://doi.org/10.1080/13607863.2012.747083

Barulli, D., & Stern, Y. (2013). Efficiency, capacity, compensation, maintenance, plasticity: emerging concepts in cognitive reserve. *Trends in Cognitive Sciences*, *17*(10), 502-509. https://doi.org/10.1016/j.tics.2013.08.012

Besser, L. M., Chang, L. C., Evenson, K. R., Hirsch, J. A., Michael, Y. L., Galvin, J. E., Rapp, S. R., Fitzpatrick, A. L., Heckbert, S. R., Kaufman, J. D., & Hughes, T. M. (2021a). Associations Between Neighborhood Park Access and Longitudinal Change in Cognition in Older Adults: The Multi-Ethnic Study of Atherosclerosis. *Journal of Alzheimer's disease: JAD*, *82*(1), 221-233. https://doi.org/10.3233/jad-210370Besser, L. M., Chang, L. C., Hirsch, J. A., Rodriguez, D. A., Renne, J., Rapp, S. R., Fitzpatrick, A. L., Heckbert, S. R., Kaufman, J. D., & Hughes, T. M. (2021b). Longitudinal Associations between the Neighborhood Built Environment and Cognition in US Older Adults: The Multi-Ethnic Study of Atherosclerosis. *International Journal of Environmental Research and Public Health*, *18*(15), 7973. https://doi.org/10.3390/ijerph18157973.

Besser, L. M., McDonald, N. C., Song, Y., Kukull, W. A., & Rodriguez, D. A. (2017). Neighborhood Environment and Cognition in Older Adults: A Systematic Review. *American Journal of Preventive Medicine*, *53*(2), 241-251. https://doi.org/10.1016/j.amepre.2017.02.013

Boyle, R., Jollans, L., Rueda-Delgado, L. M., Rizzo, R., Yener, G. G., McMorrow, J. P., Knight, S. P., Carey, D., Robertson, I. H., Emek-Savaş, D. D., Stern, Y., Kenny, R.

A., & Whelan, R. (2021). Brain-predicted age difference score is related to specific cognitive functions: a multi-site replication analysis. *Brain Imaging and Behavior*, *15*(1), 327-345. https://doi.org/10.1007/s11682-020-00260-3

Cassarino, M., & Setti, A. (2015). Environment as 'Brain Training': A review of geographical and physical environmental influences on cognitive ageing. *Ageing Research Reviews*, *23*, 167-182. https://doi.org/10.1016/j.arr.2015.06.003

Cerin, E. (2019). Building the evidence for an ecological model of cognitive health. *Health & Place*, *60*, 102206. https://doi.org/10.1016/j.healthplace.2019.102206

Cerin, E., Barnett, A., Shaw, J. E., Martino, E., Knibbs, L. D., Tham, R., Wheeler, A. J., & Anstey, K. J. (2022). Urban Neighbourhood Environments, Cardiometabolic Health and Cognitive Function: A National Cross-Sectional Study of Middle-Aged and Older Adults in Australia. *Toxics*, *10*(1). https://doi.org/10.3390/toxics10010023

Cerin, E., Barnett, A., Shaw, J. E., Martino, E., Knibbs, L. D., Tham, R., Wheeler, A. J., & Anstey, K. J. (2021). From urban neighbourhood environments to cognitive health: a cross-sectional analysis of the role of physical activity and sedentary behaviours. *BMC Public Health*, *21*(1), 2320. https://doi.org/10.1186/s12889-021-12375-3

Cerin, E., Van Dyck, D., Zhang, C. J. P., Van Cauwenberg, J., Lai, P.-c., & Barnett, A. (2020). Urban environments and objectively-assessed physical activity and sedentary time in older Belgian and Chinese community dwellers: potential pathways of influence and the moderating role of physical function. *International Journal of Behavioral Nutrition and Physical Activity*, *17*(73), 1-15. https://doi.org/10.1186/s12966-020-00979-8

Cerin, E., Nathan, A., van Cauwenberg, J., Barnett, A., Barnett, D. W., the Council on CEPA (2017). The neighbourhood physical environment and active travel in older adults: a systematic review and meta-analysis. *International Journal of Behavioral Nutrition and Physical Activity*, *14*(15), 1-23. https://doi.org/10.1186/s12966-017-0471-5

Chan, O. F., Liu, Y., Guo, Y., Lu, S., Chui, C. H. K., Ho, H. C., Song, Y., Cheng, W., Chiu, R. L. H., Webster, C., & Lum, T. Y. S. (2022). Neighborhood built environments and cognition in later life. *Aging & Mental Health*, 1-9. https://doi.org/10.1080/13607863.2022.2046697

Chen, C-L., Kuo, M-C., Chen, P-Y., Tung, Y-H., Hsu, Y-C., Huang, C-W. C., Chan, W. P., & Tseng, W-Y. I. (2022). Validation of neuroimaging-based brain age gap as a mediator between modifiable risk factors and cognition. *Neurobiology of Aging*, *114*, 61-72. https://doi.org/10.1016/j.neurobiolaging.2022.03.006

Chen, J-C., Wang, X., Wellenius, G. A., Serre, M. L., Driscoll, I., Casanova, R., McArdle, J. J., Manson, J. E., Chui, H. C., & Espeland, M. A. (2015). Ambient Air Pollution and Neurotoxicity on Brain Structure: Evidence From Women's Health Initiative Memory Study. *Annals of Neurology*, *78*(3), 466-476. https://doi.org/10.1002/ana.24460

Cherrie, M. P. C., Shortt, N. K., Mitchell, R. J., Taylor, A. M., Redmond, P., Thompson, C. W., Starr, J. M., Deary, I. J., & Pearce, J. R. (2018). Green space and cognitive ageing: A retrospective life course analysis in the Lothian Birth Cohort 1936. *Social Science & Medicine*, *196*, 56-65. https://doi.org/10.1016/j.socscimed.2017.10.038

Christensen, G. M., Li, Z., Pearce, J., Marcus, M., Lah, J. J., Waller, L. A., Ebelt, S., & Hüls, A. (2022). The complex relationship of air pollution and neighborhood socioeconomic status and their association with cognitive decline. *Environment International*, *167*, 107416. https://doi.org/10.1016/j.envint.2022.107416

Clarke, P. J., Weuve, J., Barnes, L., Evans, D. A., & Mendes de Leon, C. F. (2015). Cognitive decline and the neighborhood environment. *Annals of Epidemiology*, *25*(11), 849-854. https://doi.org/10.1016/j.annepidem.2015.07.001

Clarke, P., Morenoff, J., Debbink, M., Golberstein, E., Elliott, M. R., Lantz, P. M. (2014). Cumulative Exposure to Neighborhood Context: Consequences for Health Transitions Over the Adult Life Course. *Research on Aging*, *36*(1), 115-42. https://doi.org/10.1177/0164027512470702

Clarke, P. J., Ailshire, J. A., House, J. S., Morenoff, J. D., King, K., Melendez, R., & Langa, K. M. (2012). Cognitive function in the community setting: the neighbourhood as a source of 'cognitive reserve'? *Journal Epidemiology and Community Health*, *66*(8), 730-736. https://doi.org/10.1136/jech.2010.128116

Crossman, S., & Li, O. (2015). Surface Hydrology Polygons (National). Canberra: Geoscience Australia.

de Keijzer, C., Tonne, C., Basagaña, X., Valentín, A., Singh-Manoux, A., Alonso, J., Antó Josep, M., Nieuwenhuijsen Mark, J., Sunyer, J., & Dadvand, P. (2018). Residential Surrounding Greenness and Cognitive Decline: A 10-Year Follow-up of the Whitehall II Cohort. *Environmental Health Perspectives*, *126*(7), 077003. https://doi.org/10.1289/EHP2875

de Lange, A.-M. G., Anatürk, M., Rokicki, J., Han, L. K. M., Franke, K., Alnæs, D., Ebmeier, K. P., Draganski, B., Kaufmann, T., Westlye, L. T., Hahn, T., & Cole, J. H. (2022). Mind the gap: Performance metric evaluation in brain-age prediction. *Human Brain Mapping*, *43*(10), 3113-3129. https://doi.org/10.1002/hbm.25837

Delis, D. C, Kramer, J. H, Kaplan, E., & Ober, B. A. (1987). *California Verbal Learning Test*. San Antonio: Psychological Corporation Harcourt Brace Jovanovich.

Domenech-Cebrían, P., Martinez-Martinez, M., & Cauli, O. (2019). Relationship between mobility and cognitive impairment in patients with Alzheimer's disease. *Clinical Neurology and Neurosurgery*, *179*, 23-29. https://doi.org/10.1016/j.clineuro.2019.02.015

Duan, J., Lv, Y.-B., Gao, X., Zhou, J.-H., Kraus, V. B., Zeng, Y., Su, H., & Shi, X.-M. (2020). Association of cognitive impairment and elderly mortality: differences between two cohorts ascertained 6-years apart in China. *BMC Geriatrics*, *20*(1), 29. https://doi.org/10.1186/s12877-020-1424-4

Dunstan, D. W., Zimmet, P. Z., Welborn, T. A., Cameron, A. J., Shaw, J., de Courten, M., Jolley, D., & McCarty, D. J. (2002). The Australian Diabetes, Obesity and Lifestyle Study (AusDiab) - methods and response rates. *Diabetes Research and Clinical Practice*, *57*(2), 119-129. https://doi.org/10.1016/S0168-8227(02)00025-6

Elder, A., & Oberdörster, G. (2006). Translocation and effects of ultrafine particles outside of the lung. *Clinics in Occupational and Environmental Medicine*, *5*, 785–796. https://doi.org/10.1016/j.coem.2006.07.003

Finlay, J., Esposito, M., Langa, K. M., Judd, S., & Clarke, P. (2022). Cognability: An Ecological Theory of neighborhoods and cognitive aging. *Social Science & Medicine*, *309*, 115220. https://doi.org/10.1016/j.socscimed.2022.115220

Finlay, J., Esposito, M., Li, M., Colabianchi, N., Zhou, H., Judd, S., & Clarke, P. (2021). Neighborhood active aging infrastructure and cognitive function: A mixed-methods study of older Americans. *Preventive Medicine*, *150*, 106669. https://doi.org/10.1016/j.ypmed.2021.106669

Friendship, O. (2021). Our ageing population and the constraints on state power. *Quadrant*, *65*(4), 32-36. https://doi.org/10.3316/informit.677084928206924

Giles-Corti, B., Moudon, A. V., Lowe, M., Cerin, E., Boeing, G., Frumkin, H., Salvo, D., Foster, S., Kleeman, A., Bekessy, S., de Sá, T. H., Nieuwenhuijsen, M., Higgs, C., Hinckson, E., Adlakha, D., Arundel, J., Liu, S., Oyeyemi, A. L., Nitvimol, K., & Sallis, J. F. (2022). What next? Expanding our view of city planning and global health and implementing and monitoring evidence-informed policy. *The Lancet Global Health*, *10*(6), e919-e926. https://doi.org/10.1016/S2214-109X(22)00066-3

Harada, C. N., Natelson Love, M. C., & Triebel, K. L. (2013). Normal cognitive aging. *Clinics in Geriatric Medicine*, *29*(4), 737-752. https://doi.org/10.1016/j.cger.2013.07.002

Ihle, A., Gabriel, R., Oris, M., Gouveia É, R., Gouveia, B. R., Marques, A., Marconcin, P., & Kliegel, M. (2022). Cognitive Reserve Mediates the Relation between Neighborhood Socio-Economic Position and Cognitive Decline. *Dementia and geriatric cognitive disorders extra*, *12*(2), 90-93. https://doi.org/10.1159/000521905

Jankowska-Kieltyka, M., Roman, A., & Nalepa, I. (2021). The Air We Breathe: Air Pollution as a Prevalent Proinflammatory Stimulus Contributing to Neurodegeneration. *Frontiers in Cellular Neuroscience*, *15*, 1-19. https://doi.org/10.3389/fncel.2021.647643

Jimenez, M. P., Elliott, E. G., DeVille, N. V., Laden, F., Hart, J. E., Weuve, J., Grodstein, F., & James, P. (2022). Residential Green Space and Cognitive Function in a Large Cohort of Middle-Aged Women. *JAMA Network Open*, *5*(4), e229306-e229306. https://doi.org/10.1001/jamanetworkopen.2022.9306

Kaplan, S. (1995). The restorative benefits of nature: Toward an integrative framework. *Journal of Environmental Psychology*, *15*(3), 169-182. https://doi.org/10.1016/0272-4944(95)90001-2

Knibbs, L. D., van Donkelaar, A., Martin, R. V., Bechle, M. J., Brauer, M., Cohen D. D., Cowie, C. T., Dirgawati, M., Guo, Y., Hanigan, I. C., Johnson, F. H., Marks, G. B., Marshall, J. D., Pereira, G., Jalaludin, B., Heyworth, J. S., Morgan, G. G., & Barnett, A. G. (2018). Satellite-Based Land-Use Regression for Continental-Scale Long-Term

Ambient PM2.5 Exposure Assessment in Australia. *Environmental Science & Technology*, *52*(21),12445-55. https://doi.org/10.1021/acs.est.8b02328

Knibbs, L. D., Coorey, C. P., Bechle, M. J., Cowie, C. T., Dirgawati, M., Heyworth, J. S., Marks, G. B., Marshall, J. D., Morawska, L., Pereira, G., & Hewson, M. G. (2016). Independent Validation of National Satellite-Based Land-Use Regression Models for Nitrogen Dioxide Using Passive Samplers. *Environmental Science & Technology*, *50*(22), 12331-12338. https://doi.org/10.1021/acs.est.6b03428

Knibbs, L. D., Hewson, M. G., Bechle, M. J., Marshall, J. D., & Barnett, A. G. (2014). A national satellite-based land-use regression model for air pollution exposure assessment in Australia. *Environmental Research*, *135*, 204-11. https://doi.org/10.1016/j.envres.2014.09.011

Kuhn, M. (2008). Building Predictive Models in R Using the caret Package. *Journal of Statistical Software*, *28*(5), 1 - 26. https://doi.org/10.18637/jss.v028.i05

McDougall, C. W., Hanley, N., Quilliam, R. S., Bartie, P. J., Robertson, T., Griffiths, M., & Oliver, D. M. (2021). Neighbourhood blue space and mental health: A nationwide ecological study of antidepressant medication prescribed to older adults. *Landscape and Urban Planning*, *214*, 104132. https://doi.org/10.1016/j.landurbplan.2021.104132

Park, J. H., Cho, H. E., Kim, J. H., Wall, M. M., Stern, Y., Lim, H., Yoo, S., Kim, H. S., & Cha, J. (2020). Machine learning prediction of incidence of Alzheimer's disease using large-scale administrative health data. *npj Digital Medicine*, *3*(1), 46. https://doi.org/10.1038/s41746-020-0256-0

Pase, M. P., Rowsthorn, E., Cavuoto, M. G., Lavale, A., Yassi, N., Maruff, P., Buckley, R. F., & Lim, Y. Y. (2022). Association of Neighborhood-Level Socioeconomic Measures With Cognition and Dementia Risk in Australian Adults. *JAMA Network Open*, *5*(3), e224071-e224071. https://doi.org/10.1001/jamanetworkopen.2022.4071

Poudel, R. G., Barnett, A., Akram, M., Martino, E., Knibbs, L. D. Anstey, K. J., Shaw, J. E., & Cerin, E. (2022). Machine Learning for Prediction of Cognitive Health in Adults Using Sociodemographic, Neighbourhood Environmental, and Lifestyle Factors. *International Journal of Environmental Research and Public Health*, *19*(17), 1-14. https://doi.org/10.3390/ijerph191710977

PSMA Australia Ltd. PSMA street network; 2012.

Rachele, J. N., Sugiyama, T., Davies, S., Loh, V. H. Y., Turrell, G., Carver, A., & Cerin, E. (2019). Neighbourhood built environment and physical function among mid-to-older aged adults: A systematic review. *Health & Place*, *58*, 102137. https://doi.org/10.1016/j.healthplace.2019.05.015

Rocca, W. A., Petersen, R. C., Knopman, D. S., Hebert, L. E., Evans, D. A., Hall, K. S., Gao, S., Unverzagt, F. W., Langa, K. M., Larson, E. B., & White, L. R. (2011). Trends in the incidence and prevalence of Alzheimer's disease, dementia, and cognitive impairment in the United States. *Alzheimer's & Dementia*, *7*(1), 80-93. https://doi.org/10.1016/j.jalz.2010.11.002

Rodriguez-Loureiro, L., Gadeyne, S., Bauwelinck, M., Lefebvre, W., Vanpoucke, C., & Casas, L. (2022). Long-term exposure to residential greenness and neurodegenerative disease mortality among older adults: a 13-year follow-up cohort study. *Environmental Health*, *21*(1), 49. https://doi.org/10.1186/s12940-022-00863-x

Roe, J., Mondschein, A., Neale, C., Barnes, L., Boukhechba, M., & Lopez, S. (2020). The Urban Built Environment, Walking and Mental Health Outcomes Among Older Adults: A Pilot Study [Original Research]. *Frontiers in Public Health*, *8*. https://www.frontiersin.org/article/10.3389/fpubh.2020.575946

Saenz, J. L., Wong, R., & Ailshire, J. A. (2018). Indoor air pollution and cognitive function among older Mexican adults. *Journal of Epidemiology and Community Health*, *72*(1), 21. https://doi.org/10.1136/jech-2017-209704

Sallis, J. F., Cerin, E., Kerr, J., Adams, M. A., Sugiyama, T., Christiansen, L. B, Schipperijn, J., Davey, R., Salvo, D., Frank, L. D., De Bourdeaudhuij, I., & Owen, N. (2020). Built Environment, Physical Activity, and Obesity: Findings from the International Physical Activity and Environment Network (IPEN) Adult Study. *Annual Review of Public Health*, *41*, 119-139. https://doi.org/10.1146/annurev-publhealth-040218-043657

Settels, J., & Leist, A. K. (2021). Changes in neighborhood-level socioeconomic disadvantage and older Americans' cognitive functioning. *Health & Place*, *68*, 102510. https://doi.org/10.1016/j.healthplace.2021.102510

Sheather S. (2009). *A modern approach to regression with R*. New York, NY: Springer.

Shih, R. A., Ghosh-Dastidar, B., Margolis, K. L., Slaughter, M. E., Jewell, A., Bird, C. E., Eibner, C., Denburg, N. L., Ockene, J., Messina, C. R., & Espeland, M. A. (2011). Neighborhood Socioeconomic Status and Cognitive Function in Women. *American Journal of Public Health*, *101*(9), 1721-1728. https://doi.org/10.2105/AJPH.2011.300169

Sisco, S. M., & Marsiske, M. (2012). Neighborhood Influences on Late Life Cognition in the ACTIVE Study. *Journal of Aging Research*, 435826. https://doi.org/10.1155/2012/435826

Smith, A. (1982). *Symbol Digit Modalities Test (SDMT) manual*. Los Angeles: Western Psychological Services.

Soloveva, M. V., Jamadar, S. D., Poudel, G., & Georgiou-Karistianis, N. (2018). A critical review of brain and cognitive reserve in Huntington's disease. *Neuroscience & Biobehavioral Reviews*, *88*, 155-169. https://doi.org/10.1016/j.neubiorev.2018.03.003

Song, S., Stern, Y., & Gu, Y. (2022). Modifiable lifestyle factors and cognitive reserve: A systematic review of current evidence. *Ageing Research Reviews*, *74*, 101551. https://doi.org/10.1016/j.arr.2021.101551

Stern, Y. (2009). Cognitive reserve. *Neuropsychologia*, *47*(10), 2015-2028. https://doi.org/10.1016/j.neuropsychologia.2009.03.004

Sylvers, D. L., Hicken, M., Esposito, M., Manly, J., Judd, S., & Clarke, P. (2022). Walkable Neighborhoods and Cognition: Implications for the Design of Health Promoting Communities. *Journal of Aging and Health*, *0*(0), 1-12. https://doi.org/10.1177/08982643221075509

Tanamas, S. K., Magliano, D. J., Lynch, B. M., Sethi, P., Willenberg, L., Polkinghorne, K. R., Chadban, S., Dunstan, D., Shaw, J. E. (2013). AusDiab 2012: The Australian Diabetes, Obesity and Lifestyle Study. *Baker Heart and Diabetes Institute*, Melbourne, Australia

Tham, R., Wheeler, A. J., Carver, A., Dunstan, D., Donaire-Gonzalez, D., Anstey, K. J., Shaw, J. E., Magliano, D. J., Martino, E., Barnett, A., & Cerin, E. (2022). Associations between Traffic-Related Air Pollution and Cognitive Function in Australian Urban Settings: The Moderating Role of Diabetes Status. *Toxics*, *10*(6), 1-12. https://doi.org/10.3390/toxics10060289

Tsang, G., Xie, X., & Zhou, S. M. (2020). Harnessing the Power of Machine Learning in Dementia Informatics Research: Issues, Opportunities, and Challenges. *IEEE Reviews in Biomedical Engineering*, *13*, 113-129. doi: 10.1109/RBME.2019.2904488.

Van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: Multivariate Imputation by Chained Equations in R. *Journal of Statistical Software*, *45*, 1–67.

Van Cauwenberg, J., Nathan, A., Barnett, A., Barnett, D. W., Cerin, E., the Council on, E., & Physical Activity -Older Adults Working, G. (2018). Relationships Between Neighbourhood Physical Environmental Attributes and Older Adults' Leisure-Time Physical Activity: A Systematic Review and Meta-Analysis. *Sports Medicine*, *48*(7), 1635-1660. https://doi.org/10.1007/s40279-018-0917-1

Wang, X., Younan, D., Millstein, J., Petkus, A. J., Garcia, E., Beavers, D. P., Espeland, M. A., Chui, H. C., Resnick, S. M., Gatz, M., Kaufman, J. D., Wellenius, G., Whitsel, E. A., Manson, J. E., Rapp, S. R., & Chen, J-C. (2021). Association of lower dementia risk with improved air quality in older women. *Alzheimer's & Dementia*, *17*(S10), e056626. https://doi.org/10.1002/alz.056626

Watts, A., Ferdous, F., Moore, K. D., & Burns, J. M. (2015). Neighborhood Integration and Connectivity Predict Cognitive Performance and Decline. *Gerontology and Geriatric Medicine*, *1*. https://doi.org/10.1177/2333721415599141

Wood, S. N. (2017). *Generalised additive models: An introduction with R*. (2nd ed). Boca Raton, FL: Chapman & Hall/CRC.

World Health Organisation. Ageing and health: Available online: https://www.who.int/news-room/fact-sheets/detail/ageing-and-health (accessed on 6 July 2022).

Wu, Y-T., Prina, A. M., Jones, A. P., Barnes, L. E., Matthews, F. E., Brayne, C., on the behalf of the Medical Research Council Cognitive, F., & Ageing, S. (2015). Community environment, cognitive impairment and dementia in later life: results from the Cognitive Function and Ageing Study. *Age and Ageing*, *44*(6), 1005-1011. https://doi.org/10.1093/ageing/afv137

Supplementary Materials

Appendix A.

Socio-demographic characteristics: Participants were asked to self-report their age, sex, educational attainment, living arrangement status (living with partner and no children; living with partner and children; living alone; other arrangements), annual household income before taxes and ethnicity (English-speaking background vs. non-English-speaking background).

Neighbourhood self-selection: Participants were asked to report on a 5-point Likert-type scale the perceived importance of moving to their neighbourhood for the following reasons: closeness to open space (1 item); closeness to job or school (1 item); closeness to public transportation (1 item); desire for nearby shops and services (1 item); and closeness to recreational facilities (1 item).

Appendix B.

Table S1. Influx and outflux statistics (n = 3418).

Variable	pobs	influx	outflux
SA1	1	0	1
Area-level IRSAD	1	0	1
Age	1	0	1
Sex	1	0	1
Living arrangements	0.97	0.02	0.69
Ethnicity	1	0	1
Educational attainment	0.99	0.01	0.96
Household income	0.97	0.03	0.68
Residential self-selection - access to destinations	0.91	0.08	0.31
Residential self-selection - recreational facilities	0.91	0.08	0.31
Spot the Word Test	0.95	0.04	0.66
Symbol Digit Modalities Test	0.97	0.01	0.77
California Verbal Learning Test	0.97	0.02	0.76
Street intersection density (intersections/km2)	1	0	1
Population density (persons/hectare)	1	0	1
Commercial land use (%)	1	0	1
Parkland availability (%)	1	0	1

Blue space availability (%)	1	0	1
Annual average NO_2	1	0	1
Annual average $PM_{2.5}$	1	0	1
Cognitive age gap	0.84	0.14	0

Note: pobs = proportion of observed data; influx = is equal to the number of variable pairs (Y_j, Y_k) with Y_j missing and Y_k observed, divided by the total number of observed data cells. Influx of a variable with no missing data is 0, while variables with 100% of missing data have influx 1. For two variables with the same proportion of missing data, the variable with higher influx might be easier to impute because it is better connected to the observed data. Outflux is equal to the number of variable pairs with Y_j observed and Y_k missing, divided by the total number of incomplete data cells. Outflux is an indicator of the potential usefulness of Y_j for imputing other variables. Outflux of a variable without missing data is 1 and that of a variable with 100% missing data is 0. For two variables having the same proportion of missing data, the variable with higher outflux may be more useful for imputing other variables because it is better connected to the missing data.

Appendix C.

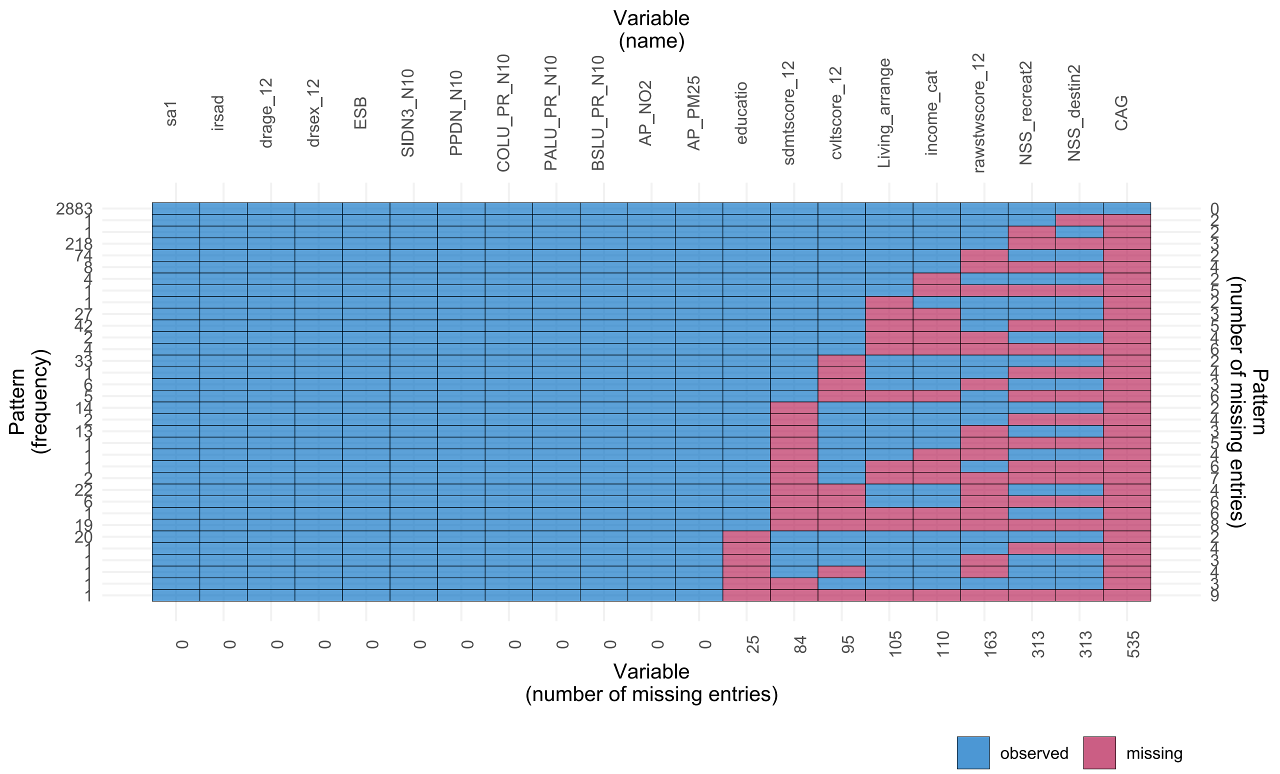

Fig. S1. Patterns of missingness (n = 3418). Data were assumed to be missing at random after examination of patterns of missingness.

Appendix D.

Table S2. Akaike information criterion values of generalised additive mixed regression models with linear and curvilinear regression terms.

Environmental attribute	Linear Model	Curvilinear Model

Population density (persons/hectare)	17690.37	17692.37
Street intersection density (intersections/km^2)	17690.18	17694.18
Percentage of commercial land use (% area in residential buffer)	17690.06	17694.06
Percentage of parkland use (% of area in residential buffer)	17682.41	17688.41
Percentage of blue space use (% of area in residential buffer)	17692.27	17696.27
Area-level socio-economic status	17682.37	17689.33
Annual average NO_2 (ppb)	17684.07	17696.07
Annual average $PM_{2.5}$ (μg/m^3)	17684.07	17696.07

Abbreviations. ppb, parts per billion; NO_2, nitrogen dioxide; $PM_{2.5}$, particulate matter with diameters of 2.5 micrometres or smaller.
Smaller Akaike information criterion values indicate a better fitting model.
Regression analyses performed on complete cases (n = 2883).

Appendix E.

Table S3. Outline of regression analyses: Estimation of total effects of environmental attributes on cognitive age gap.

Step	Exposure(s) / effect(s)	Confounders and covariates	Regression models
1Ta	Population density (persons/hectare)	Age, sex, English-speaking background, living arrangements, educational attainment, residential self-selection related to access to destinations and recreational facilities, household income	Two GAMMs (one GAMM with a linear and another with a smooth term for each environmental attribute). GAMMs with Gaussian variance and identity link functions were used for the regression analyses.
1Tb	Street intersection density (intersections/km^2)	Age, sex, English-speaking background, educational attainment, household income, living arrangements, population density, residential self-selection related to access to destinations and recreational facilities	As above
1Tc	Percentage of commercial land use (% area in residential buffer)	Age, sex, English-speaking background, household income, living arrangements, educational attainment, population density, residential self-selection related to access to destinations and recreational facilities	As above

Step	Exposure(s) / effect(s)	Confounders and covariates	Regression models
1Td	Percentage of parkland (% of area in residential buffer)	Age, sex, English-speaking background, educational attainment, household income, living arrangements, population density, percentage of commercial land use, residential self-selection related to destinations and recreational facilities	As above
1Te	Percentage of blue space (% of area in residential buffer)	Age, sex, English-speaking background, educational attainment, residential self-selection related to destinations and recreational facilities, household income, living arrangements, population density	As above
1Tf	Area-level socio-economic status (SES)	Age, sex, living arrangements, household income, percentage of blue space, percentage of commercial land use, English-speaking background, educational attainment, percentage of parkland use, population density, street intersection density, residential self-selection related to destinations and recreational facilities	As above
1Tg	Annual average NO_2 (ppb)	Age, sex, English-speaking background, household income, living arrangements, educational attainment, population density, area-level SES, street intersection density, percentage of commercial land use, percentage of parkland, residential self-selection related to destinations and recreational facilities	As above
1Th	Annual average $PM_{2.5}$ ($\mu g/m^3$)	Age, sex, English-speaking background, household income, living arrangements, educational attainment, population density, area-level SES, street intersection density, percentage of commercial land use,	As above

		percentage of parkland, residential self-selection related to destinations and recreational facilities	

Abbreviations. GAMM, generalised additive mixed model; ppb, parts per billion.
"T" in the Step refers to "total effect".

Appendix F.

Table S4. Outline of regression analyses: Estimation of direct effects of environmental attributes on cognitive age gap.

Step	Exposure(s) / effect(s)	Confounders and covariates	Regression models
2Da	Population density (persons/hectare)	Age, sex, English-speaking background, living arrangements, educational attainment, residential self-selection related to access to destinations and recreational facilities, household income, annual average NO_2 and $PM_{2.5}$, area-level SES, percentage of blue space, percentage of commercial land use, percentage of parkland use, street intersection density	Two GAMMs (one GAMM with a linear and another with a smooth term for each environmental attribute). GAMMs with Gaussian variance and identity link functions were used for the regression analyses.
2Db	Street intersection density (intersections/km^2)	Age, sex, English-speaking background, educational attainment, household income, living arrangements, population density, residential self-selection related to access to destinations and recreational facilities, annual average NO_2 and $PM_{2.5}$, area-level SES, percentage of blue space, percentage of commercial land use, percentage of parkland use	As above
2Dc	Percentage of commercial land use (% area in residential buffer)	Age, sex, English-speaking background, household income, living arrangements, educational attainment, population density, residential self-selection related to access to destinations and recreational facilities, annual average NO_2 and $PM_{2.5}$, area-level SES, percentage of blue space, percentage of parkland use, street intersection density	As above
2Dd	Percentage of parkland (% of area in residential buffer)	Age, sex, English-speaking background, educational attainment, household income, living arrangements, population density, percentage of commercial land use, residential self-selection related to destinations and recreational facilities, annual average NO_2 and $PM_{2.5}$, area-level SES, percentage of blue space, street intersection density	As above

2De	Percentage of blue space (% of area in residential buffer)	Age, area-level SES, sex, English-speaking background, educational attainment, residential self-selection related to destinations and recreational facilities, household income, living arrangements, population density, percentage of commercial land use, percentage of parkland use, street intersection density	As above
2Df	Area-level socio-economic status (SES)	Age, sex, living arrangements, household income, percentage of blue space, percentage of commercial land use, English-speaking background, educational attainment, percentage of parkland use, population density, street intersection density, residential self-selection related to destinations and recreational facilities, annual average NO_2 and $PM_{2.5}$	As above
2Dg	Annual average NO_2 (ppb)	Age, sex, English-speaking background, household income, living arrangements, educational attainment, population density, area-level SES, street intersection density, percentage of commercial land use, percentage of parkland, residential self-selection related to destinations and recreational facilities	As above
2Dh	Annual average $PM_{2.5}$ (μg/m^3)	Age, sex, English-speaking background, household income, living arrangements, educational attainment, population density, area-level SES, street intersection density, percentage of commercial land use, percentage of parkland, residential self-selection related to destinations and recreational facilities	As above

Abbreviations. GAMM, generalised additive mixed model; ppb, parts per billion. "D" in the Step refers to "direct effect".

Appendix G.

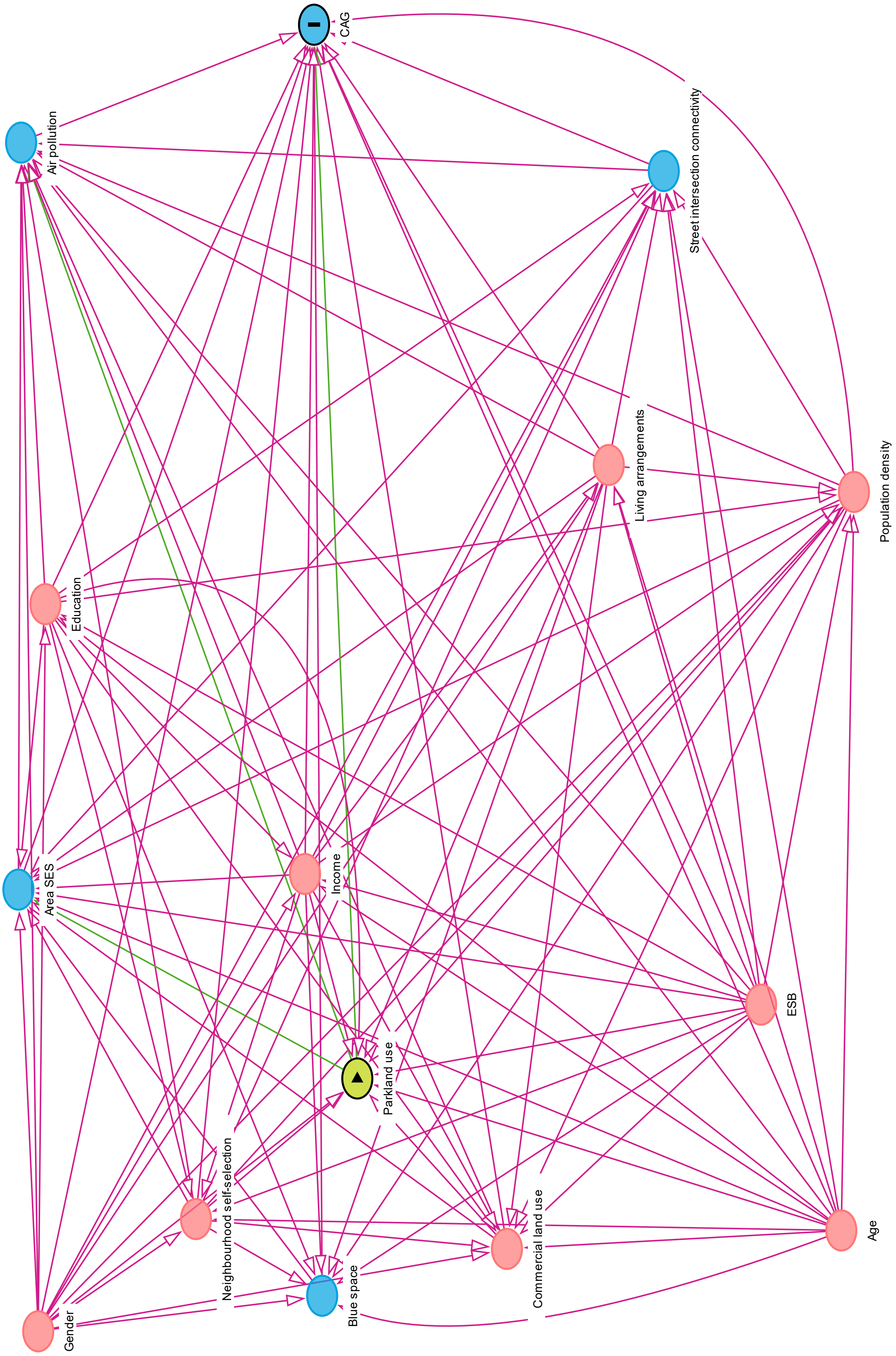
CAG
Air pollution
Street intersection connectivity
Living arrangements
Population density
Education
Area SES
Income
ESB
Parkland use
Neighbourhood self-selection
Commercial land use
Age
Blue space
Gender

Fig. S2. Directed acyclic graph (DAG) depicting the hypothesised relations between environmental attributes, socio-demographic factors and cognitive age gap Through the DAG, we identified which covariates to include in the statistical analyses to sufficiently control for potential confounders. This particular DAG was used to inform the model of the total effect of percentage of parkland in the environment on cognitive age gap. Variables with red circles denote the set of potential confounders. A minimal sufficient set of confounders (included in the regression models) is a subset of this set of variables.

A causal DAG is a graph with arrows that show the direction of hypothesised causal effects (e.g., from parkland availability to CAG). We constructed fourteen DAGs (seven for total and seven for direct effects) to estimate conjoint total and direct effects of each neighbourhood environmental attribute on cognitive age gap and, thus, help us identify a minimal set of variables that are required to be accounted for in regression models (e.g., education, gender, income and/or other environmental attributes) to ensure that estimates are unbiased. DAGs display assumptions about relationships between variables in the form of colourful nodes (= exposure variable, = adjustment variable, blue = outcome variable and = mediator) and arrows going from one node to another (red arrows represent biasing paths and green arrows indicate direct paths). The lack of an arrow represents an assumption that there is no direct causal relationship between those variables, whereas the presence of an arrow between two variables suggests that there is a direct relationship between the variables. The assumptions we make in DAGs are based on theory and empirical evidence; this particular DAG was used to inform the model of the total effect of percentage of parkland (exposure variable) in the neighbourhood environment on cognitive age gap (outcome variable). For example, there is evidence to suggest that outdoor air pollution adversely affects cognitive function (Peters et al., 2019), therefore, we need to draw an arrow from the air pollution node to the cognitive age gap node. Another example is that we have an arrow going from the Gender node to the Income node because past research has shown that, on average, men earn more than women (e.g., Forrester et al., 2020) and we have an arrow from the English-speaking background node to the CAG node, as past studies have shown the role of ethnicity in cognitive function (Meyer et al., 2021). We further hypothesised that neighbourhood population density and percentage of commercial land use would be positively related to CAG, as they provide opportunities for physical, social and cognitive activities to residents (Besser et al., 2017). The effects of percentage of parkland and blue space in the neighbourhood on CAG were expected to be positive (Besser et al., 2017; Cerin et al., 2021) and those of air pollution negative (Peters et al., 2019). Street intersection density may promote active transport (a potentially beneficial factor for cognitive health) (Besser et al., 2017) and, thus, result in lower levels of traffic-related air pollution (a harmful influence) (Zhang et al., 2019). Socio-economically advantaged neighbourhoods are associated with better cognitive health in older adults (Besser et al., 2017) and reduced risks of dementia (Pase et al., 2022) compared to neighbourhoods with lower socio-economic status. These positive associations are expected because affluent neighbourhoods provide many opportunities for individuals to engage in physical, cognitive, and social activities, and these are well-known predictors of better cognitive function (Barulli & Stern, 2013).

Appendix H.

Table S5. Total effects of environmental attributes on cognitive age gap (non-imputed data).

Environmental attribute	*b* (95% CI)	*p* value
Population density (persons/hectare)	-0.011 (-0.032, 0.009)	.28
Street intersection density (intersections/km^2)	0.006 (-0.002, 0.013)	.14
Percentage of commercial land use (% area in residential buffer)	0.025 (-0.007, 0.057)	.13
Percentage of parkland (% of area in residential buffer)	-0.026 (-0.042, -0.009)	**.002**
Percentage of blue space (% of area in residential buffer)	-0.015 (-0.107, 0.076)	.75
Area-level socio-economic status	-0.094 (-0.179, -0.009)	**.03**
Annual average NO_2 (ppb)	-0.023 (-0.156, 0.110)	.74
Annual average $PM_{2.5}$ (μg/m^3)	-0.035 (-0.167, 0.096)	.60

Abbreviations. *b*, regression coefficient; CI, confidence intervals; ppb, parts per billion.
Effects in bold are statistically significant at a probability level of 0.05.
Regression analyses performed on complete cases (n = 2883).

Appendix I.

Table S6. Direct effects of environmental attributes on cognitive age gap (non-imputed data).

Environmental attribute	*b* (95% CI)	*p* value
Population density (persons/hectare)	-0.017 (-0.047, 0.014)	.29
Street intersection density (intersections/km^2)	0.002 (-0.006, 0.009)	.62
Percentage of commercial land use (% area in residential buffer)	0.023 (-0.010, 0.057)	.17
Percentage of parkland (% of area in residential buffer)	-0.023 (-0.040, -0.006)	**.01**
Percentage of blue space (% of area in residential buffer)	-0.018 (-0.109, 0.074)	.71
Area-level socio-economic status (SES)	-0.093 (-0.180, -0.006)	**.04**
Annual average NO_2 (ppb)	-0.026 (-0.160, 0.107)	.70
Annual average $PM_{2.5}$ (µg/m^3)	-0.035 (-0.167, 0.096)	.60

Abbreviations. *b*, regression coefficient; CI, confidence intervals; ppb, parts per billion.
Effects in bold are statistically significant at a probability level of 0.05.
Regression analyses performed on complete cases (n = 2883).

Appendix J.

Table S7. Sample characteristics (n = 2883).

Characteristics	Statistic	Characteristics	Statistic
Socio-demographic characteristics		**Environmental characteristics (1km radius street-network buffers), mean (*SD*)**	
Age, years, mean (*SD*)	60.7 ± 11.1	Population density (persons/hectare)	17.3 (1.0)
Educational attainment, No. (%)		Street intersection density (intersections/ km^2)	62.1 (32.8)
Up to secondary	924 (32.0)	Percentage of commercial land use (% of area)	2.6 (6.2)
Trade, technician certificate	835 (29.0)	Percentage of parkland (% of area)	11.7 (13.0)
Associate diploma & equivalent	444 (15.4)	Percentage of blue space (% of area)	0.3 (2.0)

Bachelor degree, post-graduate diploma	680 (23.6)	Annual average NO_2 (ppb)	5.5 (2.0)
Living arrangements, No. (%)		Annual average $PM_{2.5}$ (μg/m^3)	6.3 (1.7)
Couple without children	1423 (49.4)		
Couple with children	799 (27.7)		
Other	661 (22.9)		
Residential self-selection - access to destinations, *M* ± *SD*	3.1 ± 1.4		
Residential self-selection - recreational facilities, *M* ± *SD*	3.1±1.5		
Sex, No. (%)			
Female	1611 (55.9)		
Male	1272 (44.1)		
Area-level IRSAD, mean (*SD*)	6.4 ± 2.7		
Ethnicity, No. (%)			
English-speaking background	2621 (90.9)		
Non-English-speaking background	262 (9.1)		
Household income, No. (%)			
Up to $49,999	953 (33.1)		
$50,000- $99,000	794 (27.5)		
$100,000 and over	905 (31.4)		
Does not know or refusal	231 (8.0)		

Abbreviations. M, mean; SD, standard deviation; IRSAD, Index of Relative Socioeconomic Advantage and Disadvantage; NO_2, nitrogen dioxide; $PM_{2.5}$, particulate matter <2.5 μm; environmental characteristics have no missing data.

Appendix K.

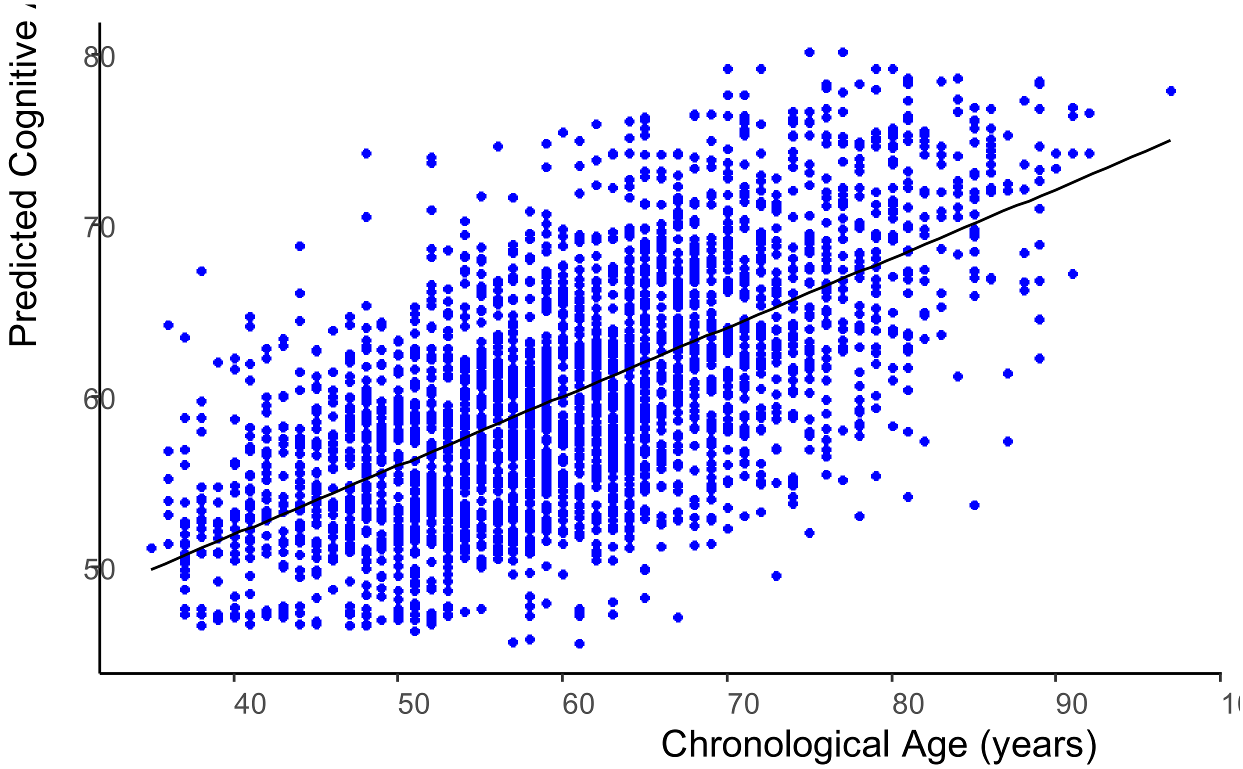

Fig. S3. Scatterplot of the correlation between predicted cognitive age and chronological age based on the testing dataset (n = 2883) The predicted value represents the prediction of cognitive age using a combination of Symbol Digit Modalities Test, California Verbal Learning Test, Spot the Word Test.

Appendix L.

Table S8. Gradient boosting machine model accuracy.

Model	R^2	RMSE	MAE	*r*
Predicted Cognitive Age	0.42	8.51	6.80	0.65

Abbreviations. Average R², coefficient of determination; RMSE, root mean square error; MAE, mean absolute error; *r*, correlation coefficient; CI, confidence intervals. Effects are statistically significant at a probability level of 0.001.

In the neuroimaging literature, the typical accuracy for the prediction of brain age varies from 2 years to 10 years in terms of mean absolute error (MAE) (Cole et al., 2017). Based on the testing dataset (n = 2883), we revealed a large correlation between predicted cognitive age and chronological age (r = 0.65) and MAE = 6.80 years, which is consistent with previous work on brain age and cognitive age (e.g., Anatürk et al., 2021).

Appendix M.

Table S9. Performance metrics of machine learning for modelling predicted cognitive age with chronological age.

Full Sample		
	MSE	72.40
	MAE	6.80
	RMSE	8.51
	R^2	0.42
	r	0.65
Sub-sample		
	MSE	53.98
	MAE	5.88
	RMSE	7.35
	R^2	0.35
	r	0.59

Appendix N.

Table S10. Performance metrics of machine learning vs linear regression.

	Machine Learning	Linear Regression
MSE	72.40	74.00
MAE	6.80	6.86
RMSE	8.51	8.60
R^2	0.42	0.40
r	0.65	0.64

Appendix O.

Table S11. Direct effects of environmental attributes on cognitive age gap.

Environmental Attribute	***b* (95% CI)**	***p* value**
Population density (persons/hectare)	-0.009 (-0.040, 0.023)	.59
Street intersection density (intersections/km^2)	0.002 (-0.006, 0.009)	.68
Percentage of commercial land use (% area in residential buffer)	0.027 (-0.007, 0.061)	.12
Percentage of parkland (% of area in residential buffer)	-0.020(-0.037, -0.003)	**.02**
Percentage of blue space (% of area in residential buffer)	-0.001 (-0.094, 0.093)	.99
Area-level IRSAD	-0.131 (-0.218, -0.044)	**.00**
Annual average NO_2 (ppb)	-0.072 (-0.208, 0.063)	.30
Annual average $PM_{2.5}$ ($\mu g/m^3$)	-0.028 (-0.161, 0.105)	.68

Abbreviations. *b*, regression coefficient; CI, confidence intervals.
Effects in bold are statistically significant at a probability level of 0.05.

Table S12. Total effects of environmental attributes on cognitive age gap.

Environmental Attribute	***b* (95% CI)**	***p* value**
Population density (persons/hectare)	-0.010 (-0.031, 0.011)	.37
Street intersection density (intersections/km^2)	0.007 (-0.001, 0.014)	.08
Percentage of commercial land use (% area in residential buffer)	0.028 (-0.005, 0.061)	.09
Percentage of parkland (% of area in residential buffer)	-0.025 (-0.041, -0.008)	**.00**
Percentage of blue space (% of area in residential buffer)	-0.002 (-0.096, 0.092)	.97
Area-level IRSAD	-0.138 (-0.223, -0.054)	**.00**
Annual average NO_2 (ppb)	-0.075 (-0.210, 0.060)	.28
Annual average $PM_{2.5}$ ($\mu g/m^3$)	-0.028 (-0.161, 0.105)	.68

Abbreviations. *b*, regression coefficient; CI, confidence intervals.
Effects in bold are statistically significant at a probability level of 0.05.

References

Anaturk, M., Kaufmann, T., Cole, J. H., Suri, S., Griffanti, L., Zsoldos, E., Filippini, N., Singh-Manoux, A., Kivimäki, M., Westlye, L. T., Ebmeier, K. P., & de Lange, A.-M. G. (2021). Prediction of brain age and cognitive age: Quantifying brain and cognitive maintenance in aging. *Human Brain Mapping*, *42*(6), 1626-1640. https://doi.org/https://doi.org/10.1002/hbm.25316

Barulli, D., & Stern, Y. (2013). Efficiency, capacity, compensation, maintenance, plasticity: emerging concepts in cognitive reserve. *Trends in Cognitive Sciences*, *17*(10), 502-509. https://doi.org/10.1016/j.tics.2013.08.012

Besser, L. M., McDonald, N. C., Song, Y., Kukull, W. A., & Rodriguez, D. A. (2017). Neighborhood Environment and Cognition in Older Adults: A Systematic Review. *American Journal of Preventive Medicine*, *53*(2), 241-251. https://doi.org/10.1016/j.amepre.2017.02.013

Cerin, E., Barnett, A., Shaw, J. E., Martino, E., Knibbs, L. D., Tham, R., Wheeler, A. J., & Anstey, K. J. (2021). From urban neighbourhood environments to cognitive health: a cross-sectional analysis of the role of physical activity and sedentary behaviours. *BMC Public Health*, *21*(1), 2320. https://doi.org/10.1186/s12889-021-12375-3

Cole, J. H., Poudel, R. P. K., Tsagkrasoulis, D., Caan, M. W. A., Steves, C., Spector, T. D., Montana, G. (2017). Predicting brain age with deep learning from raw imaging data results in a reliable and heritable biomarker. *Neuroimage*, *163*, 115-124. https://doi.org/10.1016/j.neuroimage.2017.07.059

Forrester, L. A., Seo, L. J., Gonzalez, L. J., Zhao, C., Friedlander, S., & Chu, A. Men Receive Three Times More Industry Payments than Women Academic Orthopaedic Surgeons, Even After Controlling for Confounding Variables. *Clinical Orthopaedics and Related Research*, *478*(7), 1593-1599. https://doi.org/ 10.1097/CORR.0000000000001132

Meyer, O. L., Besser, L., Mitsova, D., Booker, M., Luu, E., Tobias, M., Farias, S. T., Mungas, D., DeCarli, C., & Whitmer, R. A. (2021). Neighborhood racial/ethnic segregation and cognitive decline in older adults. *Social Science & Medicine*, *284*, 114226. https://doi.org/10.1016/j.socscimed.2021.114226

Pase, M. P., Rowsthorn, E., Cavuoto, M. G., Lavale, A., Yassi, N., Maruff, P., Buckley, R. F., & Lim, Y. Y. (2022). Association of Neighborhood-Level Socioeconomic Measures With Cognition and Dementia Risk in Australian Adults. JAMA Network Open, 5(3), e224071-e224071. https://doi.org/10.1001/jamanetworkopen.2022.4071

Peters, R., Ee, N., Peters, J., Booth, A., Mudway, I., & Anstey, K. J. (2019). Air Pollution and Dementia: A Systematic Review. *Journal of Alzheimer's Disease*, *70*, S145-S163. https://doi.org/10.3233/JAD-180631

Zhang, C. J. P., Barnett, A., Johnston, J. M., Lai, P-C., Lee, R. S. Y., Sit, C. H. P., & Cerin, E. (2019). Objectively-measured neighbourhood attributes as correlates and moderators of quality of life in older adults with different living arrangements: The ALECS cross-sectional study. *International Journal of Environmental Research and Public Health*, *16*(5), 876. https://doi.org/10.3390/ijerph16050876