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Associations of the neighbourhood built and natural environment with cardiometabolic health indicators: A cross-sectional analysis of environmental moderators and behavioural mediators

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ABSTRACT

Background: Most studies examining the effects of neighbourhood urban design on cardiometabolic health focused solely on the built or natural environment. Also, they did not consider the roles of neighbourhood socio-economic status (SES) and ambient air pollution in the observed associations, and the extent to which these associations were mediated by physical activity and sedentary behaviours.

Methods: We used data from the AusDiab3 study (N = 4141), a national cohort study of Australian adults to address the above-mentioned knowledge gaps. Spatial data were used to compute indices of neighbourhood walkability (population density, intersection density, non-commercial land use mix, commercial land use), natural environment (parkland and blue spaces) and air pollution (annual average concentrations of nitrogen dioxide (NO_2) and fine particulate matter <2.5 μm in diameter ($PM_{2.5}$)). Census indices were used to define neighbourhood SES. Clinical assessments collected data on adiposity, blood pressure, blood glucose and blood lipids. Generalised additive mixed models were used to estimate associations.

Results: Neighbourhood walkability showed indirect beneficial associations with most indicators of cardiometabolic health via resistance training, walking and sitting for different purposes; indirect detrimental associations with the same indicators via vigorous gardening; and direct detrimental associations with blood pressure. The neighbourhood natural environment had beneficial indirect associations with most cardiometabolic health indicators via resistance training and leisure-time sitting, and beneficial direct associations with adiposity and blood lipids. Neighbourhood SES and air pollution moderated only a few associations of the neighbourhood environment with physical activity, blood lipids and blood pressure.

Conclusions: Within a low-density and low-pollution context, denser, walkable neighbourhoods with good access to nature may benefit residents' cardiometabolic health by facilitating the adoption of an active lifestyle. Possible disadvantages of living in denser neighbourhoods for older populations are having limited opportunities for gardening, higher levels of noise and less healthy dietary patterns associated with eating out.

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1. Introduction

Cardiovascular diseases (CVD) top the list of causes of death in Australia (Global Burden of Disease Study 2019 Australia Collaborators, 2019) and globally (Global Burden of Disease Study, 2016). CVD risk can be reduced by tackling related cardiometabolic and behavioural risk factors. The former include obesity, elevated blood pressure, elevated blood glucose and dyslipidaemia (Dahlöf, 2010). An important behavioural risk factor for CVD and the above-mentioned cardiometabolic risk factors is physical inactivity (Balakumar et al., 2016; Cunningham et al., 2020). With 28% of adults being insufficiently physically active (Guthold et al., 2018) and 39% being overweight (Loos and Yeo, 2022) globally, large-scale, long-term sustainable interventions are required to address the high prevalence of CVD and associated risk factors.

Physical features of residential neighbourhoods, such as residential density and access to amenities and nature, have been identified as important, large-scale modifiable determinants of physical activity and health (Giles-Corti et al., 2022; World Health Organization, 2009; World Health Organisation, 2020a), especially in ageing populations (World Health Organisation, 2020a,b), who are more susceptible to CVD (World Health Organization, 2017). Neighbourhood design can impact ambient air pollution (Borrego et al., 2006; Münzel et al., 2018a,b; Wang et al., 2017) and lifestyle behaviours (physical activity and sedentary behaviours), known to affect cardiometabolic risk factors (e.g., obesity and elevated blood glucose) (An et al., 2018; Balakumar et al., 2016; Cunningham et al., 2020; Honda et al., 2017; Münzel et al., 2018a,b; Zhang et al., 2019). Specifically, it is well established that a physically active lifestyle contributes to better cardiovascular health by exerting beneficial effects on the heart (e.g., lower resting heart rate, improved mitochondrial biogenesis and greater cardiac output), blood vessels (e.g., lower resting blood pressure, vascular resistance and atherosclerotic plaque formation), blood (e.g., increased insulin sensitivity and insulin-dependent glucose uptake, better lipid profile) and by reducing systemic inflammation (Nystoriak and Bhatnagar, 2018), while exposure to ambient air pollution is deemed to harm cardiometabolic health by increasing oxidative stress and systemic inflammation (Brook, 2008).

It is, thus, important to understand how neighbourhood environments are associated with CVD risk factors and related behaviours, and how such risk factors can be reduced through urban and transport planning. In fact, suboptimal urban and transport planning resulting in higher NO_2 concentrations, carbon emissions, loss of green spaces and activity-unfriendly environments have been blamed for substantially contributing to morbidity and premature mortality (Bird et al., 2018; Mueller et al., 2021; Nieuwenhuijsen, 2020).

Studies suggest that adult residents of denser areas with better street connectivity and access to a variety of services and natural features (e.g., greenspace) tend to walk more for utilitarian purposes (Cerin et al., 2017) and, in general, be more physically active in their leisure time (Georgiou et al., 2021; Van Cauwenberg et al., 2018). There is also some evidence that, by engaging in more physical activity as a result of living in walkable, destination-rich environments, older people may reduce time spent sitting (Astell-Burt et al., 2014; Barnett et al., 2015; Cerin et al., 2020; Cerin et al., 2023b). It follows that residents of walkable neighbourhoods with good access to amenities and greenspace are likely to have better cardiometabolic health (e.g., lower probability of being overweight/obese or having elevated blood glucose) and, hence, lower risk of CVD. In fact, recent systematic reviews report beneficial effects of greenspace on CVD mortality (Liu et al., 2022) and cardiometabolic risk factors, including elevated blood pressure (Fan et al., 2022), overweight/obesity (Rahimi-Ardabili et al., 2021), elevated blood glucose and dyslipidaemia (Dendup et al., 2018; Rahimi-Ardabili et al., 2021). Similarly, access to blue space has been reported to be negatively associated with abdominal adiposity, blood glucose and dyslipidaemia (Cerin et al., 2022), but, in general, findings are mixed (Geneshka et al., 2021). In contrast, the evidence of walkable neighbourhoods (typified by higher levels of density, street connectivity and access to services) having beneficial effects on overweight/obesity, and elevated blood pressure and glucose has somewhat been more consistent (Chandrabose et al., 2019).

A major limitation of studies examining built and natural environmental correlates of CVD risk factors, and especially those focusing on neighbourhood walkability, pertains to many of them not accounting for ambient air pollution, which is a by-product of urbanisation (Cerin, 2019; James et al., 2015). Dense, destination-rich neighbourhoods that promote an active lifestyle are often accompanied by higher volumes of traffic and traffic-related air pollution (Khreis et al., 2023) that contribute to CVD (Huang et al., 2021) and related cardiometabolic (Gaio et al., 2019; Liu et al., 2019; Wang et al., 2023) and behavioural risk factors (An et al., 2019). For example, exhaust fumes from vehicles and media warnings about poor air quality may deter residents from engaging in outdoor physical activity (An et al., 2019). Conversely, the presence of greenery in a neighbourhood may reduce traffic-related air pollution (Hirabayashi and Nowak, 2016). As the neighbourhood natural and built environments impact ambient air pollution, and the latter increases the risk of CVD, to estimate the independent contribution of the neighbourhood built and natural environment on CVD and its risk factors, it is important to consider ambient air pollution. Air pollution may not only directly impact CVD cardiometabolic and behavioural risk factors, it can also determine the strength and direction of associations between the neighbourhood environment and risk factors (Howell et al., 2019), as well as associations among risk factors (e.g., physical activity and elevated blood glucose) (D'Oliveira et al., 2023; Hou et al., 2021).

Another important environmental factor that may explain CVD risk factors, as well as modify their relationships with the built and natural environment, is neighbourhood socio-economic status (SES). Neighbourhood SES has been identified as a key determinant of cardiometabolic health (Barnett et al., 2022; Carroll et al., 2020; Keita et al., 2014; Mohammed et al., 2019; Tiwari et al., 2022; Williams et al., 2012), physical activity (Cerin and Leslie, 2008; Grant et al., 2010; Tiwari et al., 2022; Zhu et al., 2021) and sedentary behaviours (Proper et al., 2007), with those living in more advantaged neighbourhoods being healthier and more physically active. However, less is known about the extent to which neighbourhood SES moderates associations between the neighbourhood environment and CVD risk factors, and between CVD behavioural risk factors and cardiometabolic risk factors. While, in their recent systematic review, Rigolon and colleagues reported stronger beneficial effects of greenspace on cardiometabolic health among residents of more disadvantaged areas (Rigolon et al., 2021), the evidence of the moderating role of neighbourhood SES in relation to other neighbourhood environmental attributes and CVD behavioural risk factors is mixed and inconclusive (Sallis et al., 2009). Understanding the relative importance of environmental and behavioural factors that contribute to cardiometabolic health in communities with different levels of social disadvantage can inform interventions aimed at reducing health inequalities, one of the key goals of the United Nations sustainable development goals agenda (United Nations, 2021).

To address the above-mentioned knowledge gaps, the aims of this cross-sectional study were three-fold. We examined: (1) associations of the neighbourhood natural and built environment with CVD cardiometabolic risk factors in mid-aged and older Australians, while adjusting for neighbourhood SES and ambient air pollution; (2) the mediating roles of domain-specific physical activity and sedentary behaviours in these associations; and (3) ambient air pollution and neighbourhood SES as moderators of environment-cardiometabolic risk factor associations and related physical activity and sedentary behaviour pathways, as depicted in Fig. 1. It is noteworthy that, according to this theoretical model, physical activity is an antecedent of sedentary behaviour because, from an evolutionary perspective, the natural tendency of adults (and older adults) is to preserve energy (i.e., be inactive) unless they have specific reasons to be active, such as performing activities of daily living or exercising for health or leisure purposes (Caldwell, 2016; Speakman, 2020). Thus, in adults and older adults, it

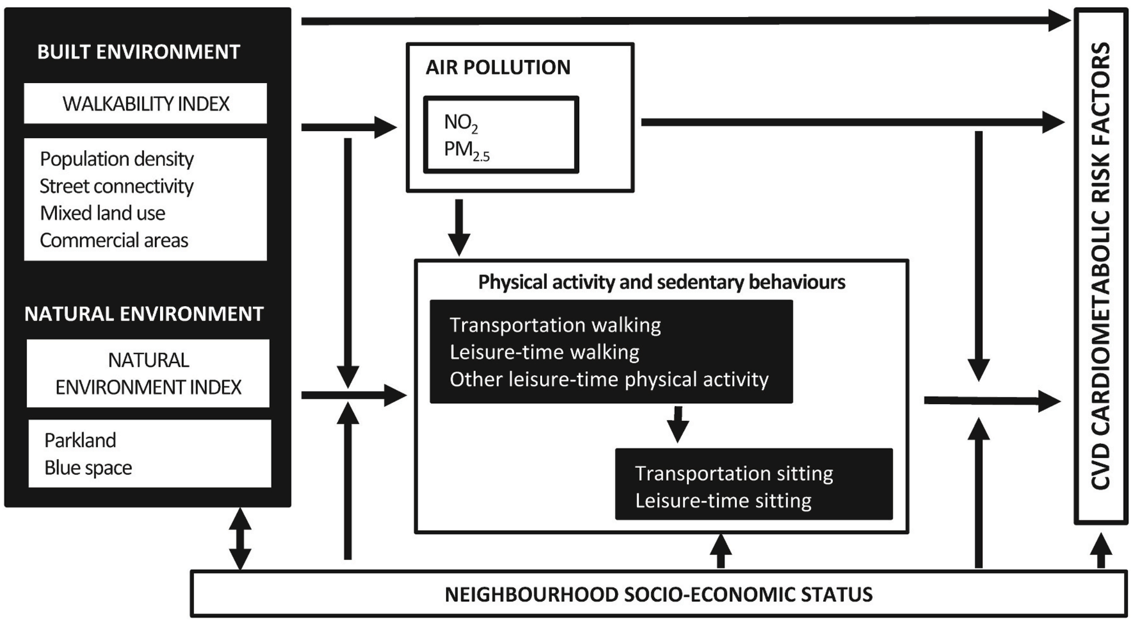

Fig. 1. Simplified model of neighbourhood environmental correlates of cardiometabolic risk factors of cardiovascular disease (CVD).

makes more sense to assume that physical activity displaces sedentary behaviour (which, from an evolutionary perspective, is the "default" behaviour) than the opposite.

2. Methods

2.1. Study design and participants

This study employed data from the third wave of the Australian Diabetes, Obesity and Lifestyle study (AusDiab3) (Dunstan et al., 2002; Tanamas et al., 2013) conducted in 2011-12 and enriched with spatial indicators of neighbourhood SES, walkability, natural environment and ambient air pollution detailed in subsection 2.2.1 (Cerin et al., 2022; Cerin et al., 2023a). Only data from AusDiab3 (N = 4614) were utilised because spatial data corresponding to earlier AusDiab waves were of inadequate quality or unavailable (Cerin et al., 2023a). The analytical sample (N = 4141) was restricted to participants who at the time of the assessment were living in urban areas (towns or cities with 10,000 or more inhabitants (ABS, 2017) consisting of 1286 Statistical Areas 1 (SA1, the smallest census administrative units in Australia).

Briefly, in 1999–2000, AusDiab recruited and examined adults (25+ years of age) with no physical or intellectual disabilities and who had resided for at least six months in one of 42 randomly-selected urban areas across Australia. Follow-up assessments were conducted in 2004-05 and 2011–12. Data collection (surveys and cardiometabolic health biomarkers) was done in person at local testing sites (Tanamas et al., 2013). AusDiab data collection procedures, and response and attrition rates have been previously reported (Dunstan et al., 2002; Tanamas et al., 2013). The AusDiab study was approved by the Alfred Hospital Ethics Committee (ref. no. 39/11) and conducted according to the guidelines of the Declaration of Helsinki. All participants provided written consent prior to partaking in the study.

2.2. Measures

2.2.1. Neighbourhood characteristics (environmental exposures)

A participant's neighbourhood was defined as an area within 1 km from their residential address following the street network, approximating the distance that an able-bodied adult can walk in 10–20 min (Adams et al., 2014). This is a frequently used neighbourhood definition (Cerin et al., 2013; Gunn et al., 2017) that, in an Australian context, has yielded stronger associations with walking behaviours than definitions of neighbouhood based on shorter (e.g., 0.5 km) or longer (e.g., 1.6 km) distances (Gunn et al., 2017). ESRI's ArcGIS v.10.5 software (ESRI, Redlands) was used to generate spatial indicators of the neighbourhood environment around participants' residential addresses, the spatial distribution of which can be found in the supplementary data (Figure S4). For sensitivity analyses purposes, we also computed spatial indicators for 500 m and 1.6 km residential buffers. Nine neighbourhood environmental characteristics were computed for each participant's neighbourhood. These included four built environment attributes [population density (persons/ha), street intersection density (intersections/km^2), percentage of commercial land use and non-commercial land use mix (an entropy score of non-commercial land uses ranging from 0 to 1)], two natural environment attributes (percentage of parkland and percentage of blue space), neighbourhood SES (Index of Relative Socio-economic Advantage and Disadvantage, IRSAD) and two ambient air pollution measures [annual average concentrations of nitrogen dioxide (NO_2, unit: ppb) and fine particulate matter <2.5 μm in aerodynamic diameter ($PM_{2.5}$; unit: μg/m^3)]. Concentrations of air pollutants were estimated at the participants' residential addresses using satellite-based land-use regression models. The models utilised spatial predictors of annual average NO_2 and $PM_{2.5}$ at fixed-site monitors (e.g., roads, industrial emissions), including time-varying information from satellites, to calculate concentrations at unmeasured locations (e.g., residential addresses) (Knibbs et al., 2014, 2016, 2018). Cross-validation revealed that the NO_2 model captured 81% of spatial variability in annual NO_2 (RMSE: 1.4 ppb), while the $PM_{2.5}$ model captured 63% of spatial variability (RMSE: 1 μg/m^3). All neighbourhood measures were based on spatial data collected during AusDiab3 assessments (2011–12). Detailed descriptions of the environmental exposures and their data sources have been published elsewhere (Cerin et al., 2021; Cerin et al., 2023a) and can be also found in the supplementary data.

For the purpose of this study, we used four composite indices representing the neighbourhood built, natural, socio-economic and air quality environments. In line with the extant literature (Cerin et al., 2016; Frank et al., 2010), we summed the standardised values of population and street intersection densities, percentage of commercial land use and non-commercial land use mix to obtain a walkability index representing the built environment. A natural environment index was computed by summing the standardised values of percentage of parkland and blue space in the neighbourhood. IRSAD is a composite measure of neighbourhood SES tailored to the Australian context and encompasses census-derived information on SES indicators such as household income, educational attainment, occupational class, housing conditions, and mortgage and rental costs (ABS, 2011). Finally, as estimates of all air pollutants typically included in air quality indices (NSW Department of Planning and Environment, n.d.) were not available, an ambient air pollution index was obtained by summing the standardized values of annual average concentrations of NO_2 and $PM_{2.5}$, which, in this study, were positively correlated (Spearman's $\rho = 0.27$).

2.2.2. Cardiometabolic health indicators (outcomes)

The outcomes of this study were a series of cardiometabolic health indicators, including an indicator of adiposity [waist circumference (in cm)], an indicator of hypertension [mean arterial blood pressure (MAP; in mmHg)], an indicator of hyperglycaemia [glycated haemoglobin (HbA1c, in mmol/mol)], and three indicators of dyslipidaemia [low-density lipoprotein (LDL) cholesterol (mmol/L), high-density lipoprotein (HDL) cholesterol (mmol/L) and triglycerides (mmol/L)]. The assessment of cardiometabolic health indicators in the AusDiab study has been previously described in detail (Dunstan et al., 2002; Tanamas et al., 2013) and is summarised in the supplementary data.

2.2.3. Physical activity and sedentary behaviours (mediators)

We used domain-specific measures of physical activity and sedentary behaviours that are deemed to be impacted by different aspects of the neighbourhood environment (Cerin et al., 2017; Van Cauwenberg et al., 2018). These included four measures of physical activity (previous-week frequencies of engagement in walking for transport, walking for recreation, vigorous gardening and resistance training) adapted from the Active Australia survey (Australian Institute of Health and Welfare, 2003), and two measures of sedentary behaviour (previous-week average daily hours of sitting time for transport and leisure) developed for AusDiab3. The leisure-time sitting measure included time spent on screen-based leisure activities (e.g., TV watching).

2.2.4. Socio-demographic and other characteristics (confounders and covariates)

Participants self-reported socio-demographic and health-related information, including age, educational attainment (up to secondary; trade or technician certificate; associate diploma or equivalent; bachelor degree or post-graduate diploma), employment status (not working; paid employment; volunteer), ethnicity (English vs. non-English background), history of heart problems or stroke (yes; no), annual household income (<AUD 50,000; AUD 50,000 to AUD 99,999; ≥AUD 100,000), living arrangements (living with partner and no children; living with partner and children; living alone; other living arrangements), medications (diabetes medication; anti-hypertensive medication; blood-lipid lowering medication), sex (female; male) and tobacco smoking status (current smoker; past smoker; never smoked). Residential self-selection was assessed with two variables based on participants' responses to items (on a 5-point scale, ranging from "not at all important" to "very important") gauging the importance of access to recreational facilities and a variety of destinations for choosing to live in the current neighbourhood (Cerin et al., 2007; Owen et al., 2007).

2.3. Statistical analyses

Descriptive statistics, including patterns of missing data, were first computed for all variables. Given that a substantial percentage (17%) of participants had missing data on at least one variable and data were not missing completely at random (e.g., missingness was related to participants' age, household income, IRSAD and population density) (Cerin et al., 2021, 2022), 20 imputed datasets were created using chained equations. Multiple imputations were performed using the package 'mice' (van Buuren and Groothuis-Oudshoorn, 2011) in R version 4.2.0 (R Core Team, 2018).

To estimate potentially-curvilinear associations of environmental exposures with cardiometabolic health indicators (Cerin et al., 2021, 2022) and examine the mediating roles of physical activity and sedentary behaviours, we employed generalised additive mixed models (GAMMs; package 'mgcv' version 1.8.42 in R) (Wood, 2017) with appropriate variance and link functions and random intercepts accounting for spatial clustering at the SA1 level (Wood, 2017). We used GAMMs with Gaussian variance and identity link functions to model waist circumference, MAP and LDL cholesterol. These models produce regression coefficients, b, indicating the difference in the response variable associated with a 1 unit increase in the explanatory variable. Gamma variance and logarithmic link functions were used to model glycated haemoglobin, HDL cholesterol, triglycerides, sitting for different purposes and non-zero frequency of physical activity behaviours. The regression coefficients of these models were exponentiated (e^b) so that they can be interpreted as the proportional increase (if $e^b >$ 1.0) or decrease (if $e^b < 1.0$) in the response variable associated with a 1 unit increase in the explanatory variable. Lastly, we employed GAMMs with binomial variances and logit link functions to model engagement (yes vs. no) in specific physical activities. The exponentiated values of the regression coefficients of these models are odds ratios (OR). Directed acyclic graphs (DAGs), based on previous studies and the authors' expert opinion, guided the selection of a minimal sufficient set of confounders for the regression models (Figure S1 and Table S1). We determined multicollinearity based on the Variance Inflation Factor (VIF) values of the variables included in the GAMMs. All VIFs were smaller than 2.44, suggesting no substantial multicollinearity (Sheather, 2019).

A first set of models examined the independent effects of the neighbourhood built (walkability index), natural (natural environment index), socio-economic (IRSAD) environments and ambient air pollution (air quality index) on cardiometabolic health indicators. Within these models, we also tested the moderating effects of medications on the environment-outcome associations and retained interaction terms that were statistically significant at a 0.05 probability level. Here, the word 'effect' is used as a statistical term (i.e., association) that does not provide evidence of causality. Given that air pollution may mediate the associations between other environmental attributes and cardiometabolic health (see Fig. 1), we also estimated associations unadjusted for the ambient air pollution index as supplementary analyses.

A second set of models examined IRSAD and the ambient air pollution index as moderators of the associations between the walkability and natural environment indices and cardiometabolic health indicators by adding two- and three-way interaction terms (and four-way interaction terms in the case of moderation by medication) to the second set of models and retaining the interaction terms that were statistically significant at a 0.05 probability level. Statistically significant moderation effects were probed by estimating the associations of the exposures (walkability or natural environment indices) with the cardiometabolic outcomes at different values of the moderators (IRSAD and ambient air pollution index).

To examine the roles of physical activity and sedentary behaviours as potential mediators of the above associations and moderating effects, we employed the joint-significant test (MacKinnon and Luecken, 2008). We decided to use this test of mediation for multiple reasons. In simulation studies, the joint-significance test displayed the best balance of Type I error and statistical power compared to other tests, such as the product-of-coefficient test derived from structural equation modelling software (MacKinnon and Luecken, 2008). This was an important consideration because the statistical effects of environmental attributes on behaviours and CVD risk factors are typically small and require statistically powerful methods of mediation. Secondly, this study examined multiple mediators. Hence, selecting a test with reasonable Type I error rates was important. Thirdly, because all physical activity mediating variables were zero inflated, they required to be modelled as two-part distributions. At present, generalised structural equation models can accommodate zero inflated outcomes but not zero inflated mediators.

Counterfactual-based mediation analysis can accommodate single zero inflated mediators with normally distributed outcomes but not multiple zero inflated mediators or single zero inflated mediators with outcomes following other distributional assumptions (Jiang et al., 2023).

According to the joint-significance test, mediation of a main effect is statistically confirmed if exposure-mediator, exposure-adjusted mediator-outcome and, in the case of serial mediation, mediator-mediator associations are statistically significant. Mediation of a moderation effect (mediated moderation) is confirmed if (1) the moderator of an exposure-outcome association is also a moderator of the exposure-mediator association and the exposure-adjusted mediator-outcome association is statistically significant; or (2) the exposure-mediator association is statistically significant and the moderator of an exposure-outcome association is also a moderator of the exposure-adjusted mediator-outcome association (Cerin et al., 2018; Muller et al., 2005). Here, exposure-outcome associations mediated by physical activity and/or sedentary behaviours are referred to as indirect statistical effects or associations, while those not mediated by these behaviours represent direct statistical effects or associations. Estimates of direct associations between exposures and outcomes were derived from regression models (separate models for each outcome) adjusted for all mediators (and confounders), which, in this case, were measures of physical activity and sedentary behaviours. Indirect associations were inferred from regression models estimating exposure-mediator and mediator-mediator (here, physical activity-sedentary behaviour) associations (separate models for each mediator), and regression models estimating exposure-adjusted mediator-outcome associations (separate models for each outcome). It is important to note that, although appropriate for the type of data examined in this study, unlike the product-of-coefficient, structural equation models and the counterfactual framework (Dzhambov et al., 2020), the joint-significant test does not explicitly quantify the indirect effects of exposures on the outcome, i.e., it does not provide a point estimate and standard error of the effect of an exposure on the outcome via a specific mediator or series of mediators (Cerin, 2010). This is a limitation. However, similarly to the product-of-coefficient test and structural equation models (Dzhambov et al., 2020), it can determine parallel and serial mediation processes and does not require significant total environment-outcome associations to establish mediation (Cerin, 2010).

3. Results

Table 1 shows the characteristics of the analytic sample. Participants were mainly middle-aged or older adults (82% aged 50+ years) of English-speaking background. The sample was diverse in household income, educational attainment and neighbourhood environmental characteristics. For example, the ranges of the four environmental indices were −5.1 to 21.1 for the walkability index, −1.1 to 20.3 for the natural environment index, −5.0 to 7.6 for the air pollution index, and 0 to 10 for IRSAD (distributions reported in Figure S2, supplementary data). The associations between the environmental indices are reported in the supplementary file (Table S2 and Figure S3) and descriptive statistics for environmental attributes based on 500 m and 1.6 km street-network buffers can be found in the supplementary data (Table S6).

Only a small percentage of the sample reported taking medications for diabetes (6.3%), while nearly a quarter and a third of the sample were on lipid-lowering and antihypertensive medications, respectively. Walking for recreation was the most, and resistance training the least, prevalent form of physical activity. On average, participants reported 0.8 h/day of sitting for transport, with 22.8% accumulating ≥1 h/day. They also reported an average of 2.6 h/day leisure-time sitting (range: 0–15 h/day). The average scores on the residential self-selection scales were around 3.0, indicating that, on average, access to destinations and recreational facilities were “somewhat important” reasons for choosing to live in the current neighbourhood.

Table 1
Analytic sample characteristics (N = 4141).

Characteristics	Statistics	Characteristics	Statistics
Individual-level socio-demographic characteristics			
Age, years, M ± SD	61.1 ± 11.4	Sex, female, %	55.2
Educational attainment, %		Employment status, %	
Up to secondary	32.7	Not employed	30.4
Trade, technician certificate	29.1	Paid employment	52.2
Associate diploma & equiv.	14.5	Volunteering	15.1
Bachelor degree, post-graduate diploma	23.1	Missing data	2.3
Missing data	0.6	English-speaking background, %	89.9
Living arrangements, %		Household income, annual, %	
Couple without children	48.2	Up to $49,999	32.9
Couple with children	26.8	$50,000 - $99,999	26.8
Other	22.4	$100,000 and over	28.9
Missing data	2.4	Does not know or refusal	8.8
		Missing data	2.7
Residential self-selection – access to destinations, M ± SD	3.0 ± 1.4	Residential self-selection – recreational facilities, M ± SD	3.1 ± 1.5
Missing data, %	7.8	Missing data, %	7.8
Neighbourhood environmental characteristics (1 km-radius street-network buffers), M ± SD			
Population density, persons/ha	17.4 ± 10.0	Street intersection density, intersections/km^2	62.2 ± 32.2
Percentage of commercial land in residential buffer	2.5 ± 6.1	Non-commercial land use mix, entropy score (0–1)	0.14 ± 0.13
Percentage of parkland in residential buffer	11.6 ± 12.5	Percentage of blue space (waterbody) in residential buffer	0.24 ± 1.98
NO_2, ppb	5.5 ± 2.1	$PM_{2.5}$, μg/m^3	6.3 ± 1.7
NO_2, μg/m^3	10.4 ± 4.0		
Area-level IRSAD, in deciles	6.4 ± 2.7	Walkability index, sum of z-scores	0.0 ± 2.5
Natural environment index, sum of z-scores	0.0 ± 1.4	Ambient air pollution index, sum of z-scores	0.0 ± 1.6
Physical activity and sedentary behaviours			
Walking for transport		Walking for recreation	
Times per week, M ± SD	1.4 ± 3.5	Times per week, M ± SD	2.4 ± 2.5
Prevalence, %	29.1	Prevalence, %	61.6
Missing data, %	2.7	Missing data, %	3.0
Vigorous gardening		Resistance training	
Times per week, M ± SD	0.8 ± 1.5	Times per week, M ± SD	0.9 ± 2.3
Prevalence, %	37.1	Prevalence, %	25.5
Missing data, %	2.6	Missing data, %	2.6
Sitting for transport, h/day, M ± SD	0.8 ± 0.8	Leisure-time sitting, h/day, M ± SD	2.6 ± 1.6
Missing data, %	2.7	Missing data, %	2.8
Cardiometabolic health indicators (outcomes)			
Mean arterial blood pressure (MAP), mmHg, M ± SD	92.0 ± 12.3	Glycated haemoglobin (HbA1C), mmol/mol, M ± SD	39.9 ± 6.3
		(HbA1C), %, M ± SD	5.8 ± 2.7
Missing data, %	0.2	Missing data, %	0.5
Waist circumference, cm, M ± SD	94.6 ± 14.2	LDL cholesterol, mmol/L, M ± SD	3.0 ± 0.9
Missing data, %	0.2	Missing data, %	1.4
HDL cholesterol, mmol/L, M ± SD	1.5 ± 0.4	Triglycerides, mmol/L, M ± SD	1.3 ± 0.9
Missing data, %	0.3	Missing data, %	0.3
Other health-related variables, %			
Diabetes medication	6.3	Tobacco-smoking status	
Missing data	1.8	Current smoker	7.0
Anti-hypertensive medication	32.0	Previous smoker	35.9
Missing data	1.8	Non-smoker	54.5
Lipid-lowering medication	24.5	Missing data	2.6
Missing data	1.8	Heart problems/stroke history	8.7
		Missing data	1.0

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; ppb, parts per billion; LDL, low-density lipoprotein; HDL, high-density lipoprotein.

3.1. Associations of neighbourhood physical environment attributes with cardiometabolic health indicators and moderating effects of neighbourhood SES and air pollution

On average, neighbourhood *walkability* was positively related to MAP (Table 2; Table S5 in the supplementary data for estimates unadjusted for ambient air pollution). However, this association depended on both neighbourhood IRSAD (SES) and ambient air pollution (walkability by IRSAD by air pollution index 3-way interaction: $b = 0.045$; 95% CI: 0.013, 0.077; $p = .007$). It was significant in high-SES neighbourhoods, irrespective of air pollution, as well as in low- and average-SES neighbourhoods with low or average ambient air pollution (Table 3). Overall, the associations were stronger in low-SES and low-air pollution neighbourhoods (Table 3). Similar moderation effects of neighbourhood IRSAD and air pollution were observed on the associations of walkability with LDL cholesterol ($b = 0.003$; 95% CI: 0.001, 0.005; $p = .012$) and triglycerides ($e^b = 1.002$; 95% CI: 1.0004, 1.003; $p = .014$). Positive relationships were found only in low-to-medium SES and low air pollution neighbourhoods (Table 3). The association of walkability with HDL cholesterol was also moderated by air pollution ($e^b = 1.002$; 95% CI: 1.0002, 1.004; $p = .030$) (Table 3). It was positive only at nearly maximum values of the air pollution index ($e^b = 1.014$; 95% CI: 1.001, 1.028; $p = .038$). The *natural environment* index was negatively related to waist circumference and LDL cholesterol (Table 2; Table S5 for estimates unadjusted for ambient air pollution). Also, it was negatively associated with HDL cholesterol in areas with high air pollution (Table 3) (natural environment index by air pollution index 2-way interaction: $e^b = 0.994$; 95% CI: 0.990, 0.998; $p = .008$).

Neighbourhood IRSAD was negatively related to waist circumference, MAP and triglycerides, and positively related to glycated haemoglobin and HDL cholesterol (Table 2; Table S5 for estimates unadjusted for ambient air pollution). Finally, the air pollution index was negatively associated with MAP and HDL cholesterol, while a positive association was observed with glycated haemoglobin (Table 2). Our data did not provide sufficient evidence of moderating effects of medication intake on any of the above associations (Table S4, supplementary data). Associations of exposures based on 500 m and 1.6 km radii street-network buffers and cardiometabolic health indicators are reported in the supplementary data (Tables S7–S10b). Overall, they were similar to those based on 1 km radius buffers. The only notable differences were 500 m buffers yielding weaker, non-significant moderating effects of ambient air pollution on the associations between the natural environment index and HDL cholesterol ($p = .440$), and 1.6 km buffers producing significantly stronger negative associations between the natural environment index and MAP (Tables S7 and S9).

3.2. Physical activity and sedentary behaviours as mediators of the associations of neighbourhood physical environment attributes with cardiometabolic health indicators

Figs. 2–6 show the indirect (behaviour-mediated) and direct (not mediated by physical activity or sedentary behaviours) associations of neighbourhood walkability and natural environment with five cardiometabolic health indicators. Significant indirect associations were found between neighbourhood walkability and all five indicators (Figs. 2–6), while direct associations emerged only with respect to MAP (Tables 4 and 5) and triglycerides (Fig. 5; Tables 4 and 5). These direct associations were respectively moderated by both IRSAD and the air pollution index, and suggestive of potential detrimental effects. Specifically, positive associations between walkability and MAP were observed in neighbourhoods with above average IRSAD irrespective of the level of air pollution, and in neighbourhoods with below average and average IRSAD that had below average and average levels of air pollution (Table 5). Walkability was also directly positively related to triglycerides, but only in neighbourhoods with below average or average IRSAD and low air pollution (Table 5).

The indirect associations of the walkability index with waist circumference, glycated haemoglobin and HDL cholesterol were mainly suggestive of potential beneficial effects via higher odds of engagement in walking for transport, walking for recreation and resistance training, and less sitting for transport and leisure-time sitting (Figs. 2–4). A similar pattern of indirect associations was also observed for triglycerides, with the exception of sitting for transport, which was unrelated to this particular cardiometabolic health indicator (Fig. 5). All indirect associations via engagement in walking for recreation appeared to be channelled through (lower) leisure-time sitting, while this did not hold for the indirect associations via engagement in walking for transport and/or resistance training in the case of waist circumference (Fig. 2), HDL cholesterol (Fig. 4) and triglycerides (Fig. 5). The indirect associations via engagement in resistance training were moderated by air pollution, whereby neighbourhood walkability was positively associated with resistance training only at above average values of the air pollution index (Figs. 2–5). The only behavioural pathways through which walkability appeared to have detrimental effects on the examined cardiometabolic health indicators were those through frequency of engagement in vigorous gardening (Figs. 2–5) and walking for transport (Fig. 6) in those engaging in these physical activities. In fact, walkability

Table 2
Associations of neighbourhood environment attributes with cardiometabolic health indicators: main effect models (unadjusted for physical activity and sedentary behaviours).

Neighbourhood environment attributes	Waist circumference (cm)	Mean arterial pressure (mmHg)	Glycated haemoglobin (mmol/mol)	HDL cholesterol (mmol/L)	LDL cholesterol (mmol/L)	Triglycerides (mmol/L)
	b (95% CI)	b (95% CI)	e^b (95% CI)	e^b (95% CI)	b (95% CI)	e^b (95% CI)
Walkability index	−0.094 (−0.295, 0.107)	**0.387 (0.174, 0.601)**	1.001 (0.999, 1.004)	1.002 (0.997, 1.007)	0.001 (−0.012, 0.014)	1.005 (0.996, 1.014)
Natural environment index	**−0.476 (-0.812, -0.140)**	−0.169 (−0.477, 0.138)	0.999 (0.996, 1.002)	1.001 (0.994, 1.007)	**−0.022 (-0.041, -0.003)**	1.000 (0.987, 1.014)
Neighbourhood IRSAD	**−0.388 (-0.581, -0.194)**	**−0.281 (-0.463, -0.098)**	**1.002 (1.001, 1.004)**	**1.009 (1.005, 1.013)**	0.011 (−0.0002, 0.022)	**0.990 (0.983, 0.997)**
Ambient air pollution index	0.335 (−0.046, 0.717)	**−0.537 (-0.877, -0.197)**	**1.004 (1.000, 1.008)**	**0.990 (0.983, 0.998)**	0.002 (−0.019, 0.022)	1.005 (0.991, 1.018)

Abbreviations: IRSAD, Index of Relative Advantage and Disadvantage; b, unstandardised regression coefficient from model with Gaussian variance and identity link functions; e^b = exponentiated regression coefficient from models with Gamma variance and logarithmic link functions; CI, confidence intervals. Estimates in bold are significant at a 0.05 two-tailed probability level. All regression coefficients are adjusted for other environmental indices, age, sex, English-speaking background, educational attainment, household income, living arrangements, work status, neighbourhood self-selection and taking medications relevant to a specific outcome (diabetes, hypertension and/or dyslipidaemia).

Table 3
Associations of neighbourhood physical environment attributes with cardiometabolic health indicators: moderating effects of neighbourhood socio-economic status and air quality (unadjusted for physical activity and sedentary behaviours).

Moderator	Moderator values	Mean arterial pressure (mmHg)	LDL cholesterol (mmol/L)	Triglycerides (mmol/L)
		b (95% CI)	b (95% CI)	e^b (95% CI)
Exposure: Walkability index				
Neighbourhood IRSAD	M − 1 SD	**0.859 (0.473, 1.246)**	**0.027 (0.002, 0.052)**	**1.024 (1.007, 1.042)**
Air pollution index	M − 1 SD			
Neighbourhood IRSAD	M − 1 SD	**0.441 (0.130, 0.753)**	0.006 (−0.014, 0.026)	1.007 (0.994, 1.021)
Air pollution index	M			
Neighbourhood IRSAD	M − 1 SD	0.024 (−0.348, 0.395)	−0.016 (−0.040, 0.009)	0.991 (0.974, 1.007)
Air pollution index	M + 1 SD			
Neighbourhood IRSAD	M	**0.665 (0.373, 0.957)**	0.012 (−0.006, 0.031)	**1.014 (1.002, 1.028)**
Air pollution index	M − 1 SD			
Neighbourhood IRSAD	M	**0.439 (0.210, 0.669)**	0.003 (−0.011, 0.017)	1.006 (0.996, 1.015)
Air pollution index	M			
Neighbourhood IRSAD	M	0.214 (−0.025, 0.453)	−0.007 (−0.022, 0.009)	0.997 (0.987, 1.008)
Air pollution index	M + 1 SD			
Neighbourhood IRSAD	M + 1 SD	**0.470 (0.056, 0.884)**	−0.002 (−0.029, 0.024)	1.005 (0.987, 1.024)
Air pollution index	M − 1 SD			
Neighbourhood IRSAD	M + 1 SD	**0.437 (0.118, 0.756)**	−0.001 (−0.020, 0.020)	1.005 (0.991, 1.018)
Air pollution index	M			
Neighbourhood IRSAD	M + 1 SD	**0.404 (0.105, 0.703)**	0.002 (−0.017, 0.021)	1.004 (0.991, 1.017)
Air pollution index	M + 1 SD			

Moderator	Moderator values	HDL cholesterol (mmol/L)
		e^b (95% CI)
Exposure: Walkability index		
Air pollution index	M − 1 SD	0.996 (0.990, 1.001)
Air pollution index	M	0.999 (0.994, 1.004)
Air pollution index	M + 1 SD	1.002 (0.997, 1.007)
Exposure: Natural environment index		
Air pollution index	M − 1 SD	1.004 (0.996, 1.011)
Air pollution index	M	0.996 (0.988, 1.003)
Air pollution index	M + 1 SD	**0.988 (0.976, 0.999)**

Abbreviations: IRSAD, Index of Relative Advantage and Disadvantage; *b*, unstandardised regression coefficient from model with Gaussian variance and identity link functions; e^b = exponentiated regression coefficient from models with Gamma variance and logarithmic link functions; CI, confidence intervals; M, mean; SD, standard deviation. Estimates in bold are significant at a 0.05 two-tailed probability level. All regression coefficients are adjusted for other environmental indices, age, sex, English-speaking background, educational attainment, household income, living arrangements, work status, neighbourhood self-selection and taking medications relevant to a specific outcome (diabetes, hypertension and/or dyslipidaemia).

was predictive of higher frequency of engagement in walking for transport and the latter was positively related to LDL cholesterol (Fig. 6). Walkability was also negatively related to frequency of vigorous gardening in those living in areas with below average or average air pollution, while a higher frequency of vigorous gardening was associated with less sitting for leisure (Figs. 2–5).

The natural environment index was negatively associated with waist circumference directly and via engagement in resistance training and leisure-time sitting (Fig. 2; Table 4). Specifically, this environmental index was positively associated with engagement in resistance training and negatively associated with leisure-time sitting, which were, in turn, directly negatively and positively related to waist circumference, respectively. Resistance training was also negatively associated with waist circumference via leisure-time sitting. Similar indirect but not direct associations were found for triglycerides (Fig. 5; Table 4). Indirect but not direct associations also emerged between the natural environment index and glycated haemoglobin (Fig. 3; Table 4). However, engagement in resistance training was negatively related to this cardiometabolic health indicator only indirectly, via leisure-time sitting (Fig. 3).

The indirect associations between the natural environment and HDL cholesterol mirrored those found for waist circumference but were, as expected, in the opposite direction because engagement in resistance training was positively, and leisure-time sitting negatively, associated with HDL cholesterol (Fig. 4). However, unlike for waist circumference, the natural environment index displayed detrimental direct associations with HDL cholesterol, albeit only for those living in neighbourhoods with above average levels of air pollution (Fig. 4; Table 5). No significant indirect associations of the natural environment index with MAP or LDL cholesterol were observed (Table 4). A direct negative association was found with LDL cholesterol (Fig. 6; Table 4).

The mediating effects of physical activity and sedentary behaviours in the associations between cardiometabolic health indicators and the neighbourhood environment indices based on the other two street-network buffers (with 500 m and 1.6 km radii) are reported in the supplementary data (Figures S5a-S9b and Tables 11a–11b). In general, the patterns of associations were similar to those observed for 1 km radius buffers, especially in relation to LDL cholesterol (Figures S9a and S9b) and triglycerides (Figure S8a). For the other cardiometabolic health indicators, mediation analyses using 500 m and 1.6 km radii buffers yielded fewer mediated effects of physical activity and/or sedentary behaviours. Specifically, when using 500 m radius buffers, sitting for transport was no longer a significant mediator of the associations of neighbourhood walkability with waist circumference, glycated haemoglobin and HDL cholesterol (Figures S5a, S6a and S7a), and engagement in resistance training was not a mediator of the associations between walkability, the natural environment index and glycated haemoglobin (Figure S6a). When using 1.6 km radius buffers, engagement in walking for recreation was no longer a mediator of the associations between walkability and waist circumference, glycated haemoglobin, HDL cholesterol and triglycerides (Figures S5b, S6b, S7b and S8b). Also, the associations between the natural environment and all these cardiometabolic health indicators were no longer directly mediated by leisure-time sitting. However, additional negative indirect effects of the natural environment index through engagement in walking for transport were observed (Figures S5b, S6b, S7b and S8b).

4. Discussion

We examined how neighbourhood built and natural environment

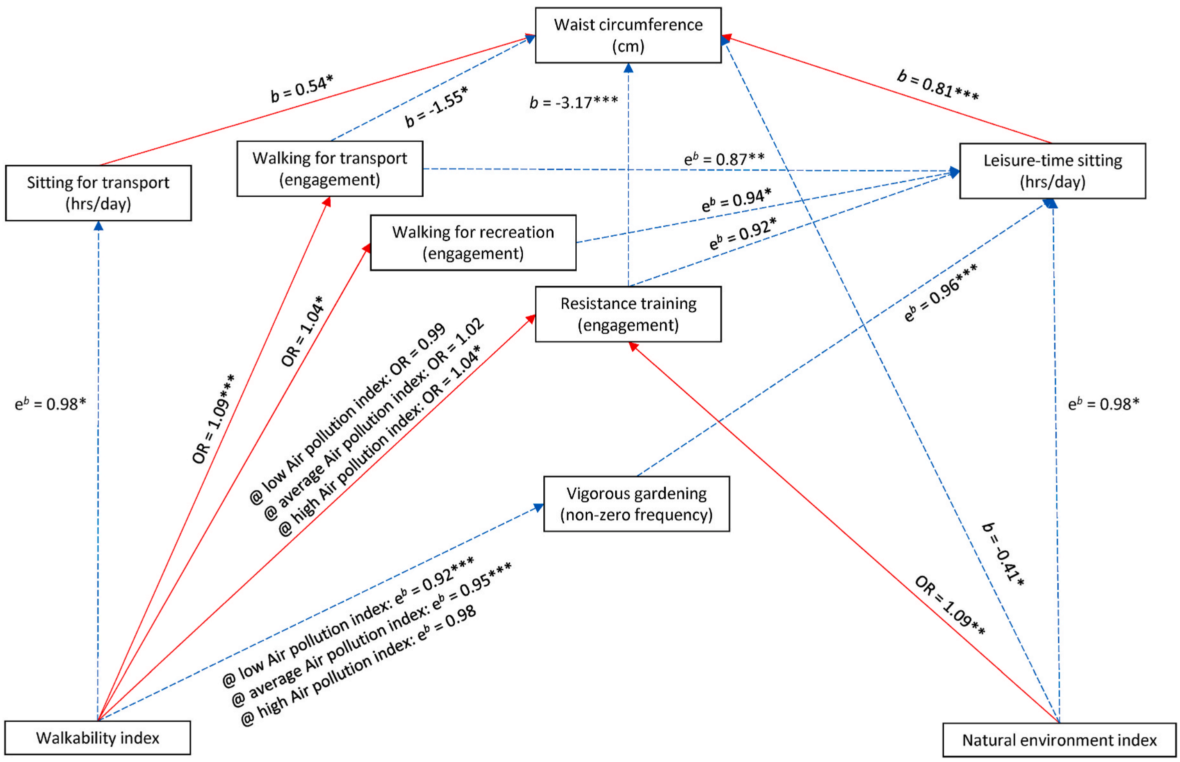

Fig. 2. Direct and indirect (behaviour-mediated) associations of the neighbourhood built and natural environment with waist circumference (cm). Arrows linking variables indicate significant associations. Red full arrows denote positive associations, while blue dashed arrows denote negative associations. @ denotes an association moderated by the Air pollution index and estimates of the association are given at different values of the Air pollution index (low = 1 standard deviation below the mean; average = mean; high = 1 standard deviation above the mean). OR = odds ratio from models with binomial variance and logit link functions (engagement in walking for different purposes and resistance training); *b* = regression coefficient from models with Gaussian variance and identify link functions (waist circumference); e^b = exponentiated regression coefficient from models with Gamma variance and logarithmic link functions (sitting for different purposes and non-zero frequency of vigorous gardening). *p < .05; **p < .01; ***p < .001. Regression coefficients and their 95% confidence intervals are presented in Table 4 and Table S2 (supplementary data). Estimates of path coefficients were obtained using a set of regression models (one for each mediator and cardiometabolic health indicator) rather than simultaneously.

characteristics are associated with cardiometabolic risk factors for CVD in Australian mid-aged and older community dwellers, and the extent to which these associations are moderated by ambient air pollution and neighbourhood SES and mediated by physical activity and sedentary behaviours. This study revealed a substantial number of associations of neighbourhood walkability and natural environment with behavioural and cardiometabolic risk factors for CVD that were in the expected direction, but also a few counterintuitive findings especially with respect to neighbourhood walkability. As the associations between neighbourhood environment attributes based on residential buffers of different sizes and cardiometabolic health indicators were similar and the mediation effects of physical activity and sedentary behaviours were, as expected (Gunn et al., 2017), stronger when neighbourhood was defined as an area within 1 km from home, our discussion focusses on the findings of exposures based on 1 km radius buffers.

4.1. Neighbourhood walkability

Higher walkability was related to less sitting for transport which, in turn, showed beneficial associations with several cardiometabolic health indicators, including waist circumference, glycated haemoglobin and HDL cholesterol. Higher walkability was also predictive of higher odds of engagement in walking for transport, walking for recreation and resistance training – behaviours that were directly and/or indirectly associated, via leisure-time sitting, with better cardiometabolic health (smaller waist circumference, higher HDL cholesterol and lower glycated haemoglobin and triglycerides). More walkable neighbourhoods appear to have a potential beneficial effect on adiposity, blood glucose and blood lipids by encouraging an active lifestyle typified by higher levels of transport and leisure-time physical activity and, through these, lower levels of transport and leisure-time sitting. In general, these findings are in line with those of previous studies on environmental correlates of physical activity (Cerin et al., 2017; Van Cauwenberg et al., 2018) and sedentary behaviours (Barnett et al., 2015; Cerin et al., 2020), and those on the effects of these behaviours on cardiometabolic health (Bai et al., 2022; Ballard et al., 2021; Chai et al., 2023; Wood et al., 2022).

A few associations between neighbourhood walkability and risk factors for CVD were counterintuitive, especially with respect to blood pressure (MAP), which was higher in more walkable neighbourhoods. The concept of neighbourhood walkability was coined by urban planners to denote urban spaces with higher levels of density, functional mix and access networks that lend themselves to a variety of transport modes and reduce car-dependence (Frank et al., 2010). As expected, and evidenced by this study, more walkable neighbourhoods typically encourage active modes of transport (e.g., walking for transport) (Cerin et al., 2017) and engagement in leisure-time physical activity (Van Cauwenberg et al., 2018), which are beneficial to cardiometabolic health (Bai et al., 2022; Ballard et al., 2021; Lee et al., 2021). However, they are also accompanied by higher levels of air pollution (James et al., 2015) and noise (Salter et al., 2015) that can be detrimental to health (Basner et al., 2014; Gaio et al., 2019; Liu et al., 2019; Salter et al., 2015; Wang et al., 2023). Although this study partially accounted for ambient air pollution, it did not account for urban noise, and this may explain the positive associations of neighbourhood walkability with MAP observed even after adjustment for antihypertensive medication. In this regard, a

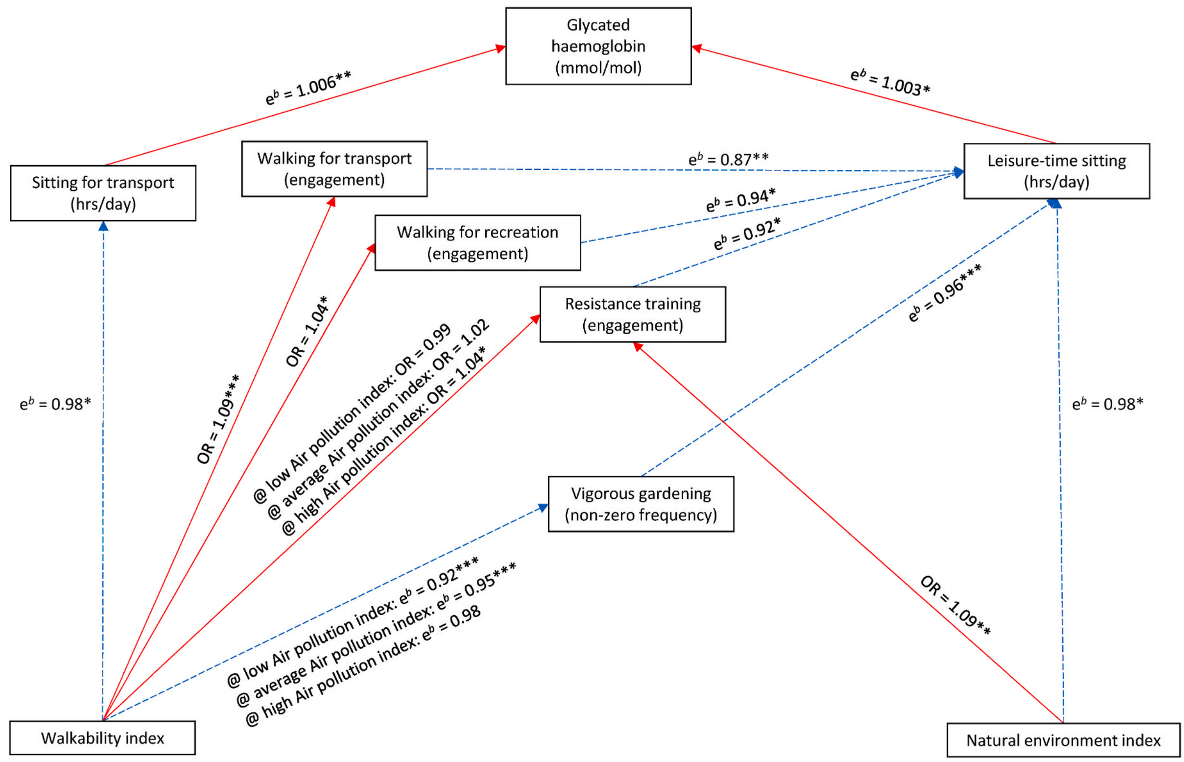

Fig. 3. Indirect (behaviour-mediated) associations of the neighbourhood built and natural environment with glycated haemoglobin (mmol/mol). Arrows linking variables indicate significant associations. Red full arrows denote positive associations, while blue dashed arrows denote negative associations. @ denotes an association moderated by the Air pollution index and estimates of the association are given at different values of the Air pollution index (low = 1 standard deviation below the mean; average = mean; high = 1 standard deviation above the mean). OR = odds ratio from models with binomial variance and logit link functions (engagement in walking for different purposes and resistance training); e^b = exponentiated regression coefficient from models with Gamma variance and logarithmic link functions (sitting for different purposes, non-zero frequency of vigorous gardening and glycated haemoglobin). *$p < .05$; **$p < .01$; ***$p < .001$. Regression coefficients and their 95% confidence intervals are presented in Table 4 and Table S2 (supplementary data). Estimates of path coefficients were obtained using a set of regression models (one for each mediator and cardiometabolic health indicator) rather than simultaneously.

large study conducted in Chicago reported that 10-dBA higher residential noise levels corresponded to over 1 mmHg greater systolic and diastolic blood pressure, as well as 20% higher odds of treatment-resistant hypertension (D'Souza et al., 2021). Sleep disruption, oxidative stress and changes in sympathetic tone triggered by affective reactions associated with exposure to noise are thought to be the main mechanisms responsible for these findings (Basner and McGuire, 2018; Münzel et al., 2018a,b). Problems arising from urban noise could be mitigated through appropriate urban and traffic planning policies (e.g., pedestrian zones, land use planning) and technological interventions (e.g., installation of double-glazed windows and road resurfacing) (Salter et al., 2015). Clearly, to understand the potential impact of dense, destination-rich neighbourhoods on various cardiometabolic risk factors for CVD, it is important to consider aspects of urban design as well as noise and air pollution exposures.

Another seemingly counterintuitive set of findings about the relationship between neighbourhood walkability and risk factors for CVD pertains to its interaction with ambient air pollution. Higher walkability was more strongly positively related to MAP, LDL cholesterol and triglycerides at lower levels of air pollution in more disadvantaged neighbourhoods. It was also more strongly negatively related to frequency of gardening at lower levels of air pollution and more strongly positively related to engagement in resistance training at higher levels of air pollution. The annual concentrations of air pollutants in the present study were generally low, i.e., less than half those observed in Europe or the U.S (Clifford et al., 2016). Within such context, it is possible that they did not significantly impact on cardiometabolic health (D'Oliveira et al., 2023) but rather acted as proxies for type and quality of neighbourhood destinations that could not be accurately captured by the coarse land use measures employed in the study. For example, we used percentage of commercial land and non-commercial land use mix as measures of access to services incorporated in the neighbourhood walkability index. However, the same percentages of commercial land might have represented popular retail and food outlets encouraging an active lifestyle and attracting visitors from other areas, or unfrequently-visited office spaces and warehouses unsupportive of an active lifestyle and of limited interest to residents from other areas. Ambient air pollution may have helped differentiate between the two types of destinations. This would explain a stronger positive association between higher walkability and engagement in resistance training at higher levels of air pollution (Figs. 2–5), as well as the more beneficial or less detrimental potential effects of walkability on some of the cardiometabolic risk factors for CVD (MAP, LDL cholesterol and HDL cholesterol) at higher levels of air pollution (Table 3), which were attenuated after adjustment for physical activity and sedentary behaviours (potential mediators) (Table 5).

The moderating effects of ambient air pollution on the associations of neighbourhood walkability with MAP, LDL cholesterol and triglycerides depended on neighbourhood SES. They were stronger in more disadvantaged neighbourhoods where higher walkability was predictive of worse cardiometabolic health outcomes at lower levels of air pollution. Residents of more disadvantaged neighbourhoods may be more dependent on their local environment as they may not afford visiting destinations outside their neighbourhoods as frequently as their socially advantaged counterparts (Holliday et al., 2017). If, in the context of the present study, air pollution was a proxy for destination relevance and quality uncaptured by the walkability index, we would expect higher neighbourhood walkability to show more beneficial associations at

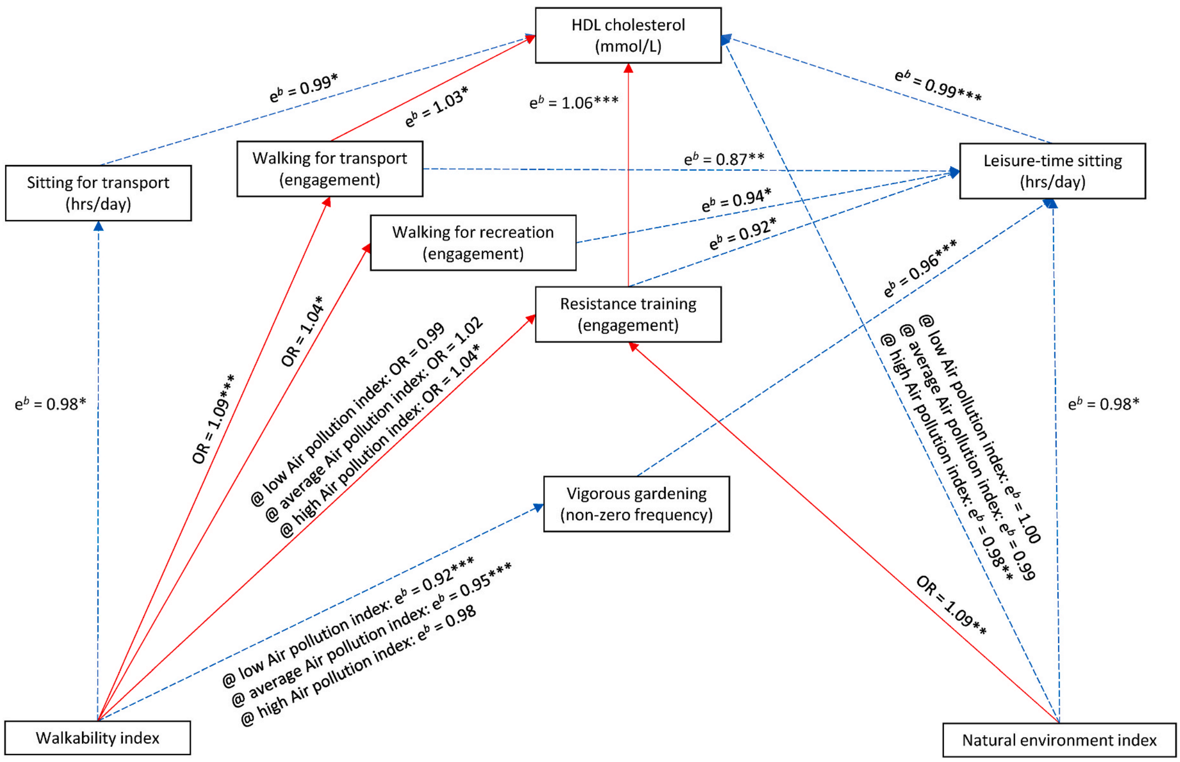

Fig. 4. Direct and indirect (behaviour-mediated) associations of the neighbourhood built and natural environment with HDL cholesterol (mmol/L). Arrows linking variables indicate significant associations. Red full arrows denote positive associations, while blue dashed arrows denote negative associations. @ denotes an association moderated by the Air pollution index and estimates of the association are given at different values of the Air pollution index (low = 1 standard deviation below the mean; average = mean; high = 1 standard deviation above the mean). OR = odds ratio from models with binomial variance and logit link functions (engagement in walking for different purposes and resistance training); e^b = exponentiated regression coefficient from models with Gamma variance and logarithmic link functions (sitting for different purposes, non-zero frequency of vigorous gardening and HDL cholesterol). *p < .05; **p < .01; ***p < .001. Regression coefficients and their 95% confidence intervals are presented in Tables 4, 5 and S2 (supplementary data). Estimates of path coefficients were obtained using a set of regression models (one for each mediator and cardiometabolic health indicator) rather than simultaneously.

higher levels of air pollution in lower SES areas. Having good quality destinations of daily living in the local area, such as a variety of food outlets and essential services, supports an active lifestyle (Cerin et al., 2017; Van Cauwenberg et al., 2018) and a healthier diet (Cooksey-Stowers et al., 2017). Dense, lower SES neighbourhoods with poor-quality destinations of daily living may have access to few low-cost, relatively unhealthy food outlets (e.g., fast food outlets, convenience stores) with a limited choice of fresh produce (Williamson et al., 2017) resulting in unhealthy dietary patterns (Mulrooney and Bell, 2016) and poorer cardiometabolic health (e.g., high LDL cholesterol and triglycerides) (Arnett et al., 2019). These findings suggest that a fine-grained characterisation of the built environment differentiating types of destinations that potentially impact cardiometabolic risk factors of CVD through key pathways (e.g., physical activity, diet) is necessary to gain a solid understanding of how neighbourhoods influence CVD.

We did not find significant moderating effects of neighbourhood SES and air pollution on the associations between behaviours and cardiometabolic risk factors, supporting the notion that being more physically active and less sedentary is beneficial to the cardiometabolic health of mid-aged and older residents living irrespective of area-level advantage and disadvantage. This is understandable given that the effects of an active lifestyle on cardiometabolic health is mainly determined by biological mechanisms (Pinckard et al., 2019) while those of the environment on cardiometabolic health may be also explained by social and behavioural factors (Barnett et al., 2022; Chandrabose et al., 2019; Rigolon et al., 2021). The lack of evidence of the moderating effect of air pollution on behaviour-health associations may be attributed to the generally low annual concentrations of air pollutants found in this study. In fact, a recent systematic review on the impact of air pollution on older adults' health while engaging in physical activity and sedentary behaviours concluded that being physically active in low-pollution environments provide health gains and reduce health risks, while this is less the case if air pollution concentrations are high (D'Oliveira et al., 2023).

A couple of additional findings pertaining to the relationships between neighbourhood walkability and CVD risk factors require consideration. In areas with low to medium air pollution, higher walkability was negatively associated with frequency of vigorous gardening which, in turn, was predictive of less sitting for leisure and, therefore, better cardiometabolic health. In general, dense, walkable areas tend to have fewer and smaller private gardens. Hence, a negative association between higher walkability and gardening was expected. The fact that this effect was not significant in neighbourhoods with higher levels of air pollution may be due to residents of low-walkable neighbourhoods avoiding spending time outdoors in their gardens despite having them. This particular finding suggests that air pollution mitigation strategies may be important to ensure older adults' participation in outdoor forms of physical activity such as gardening. In the absence of private gardens, residents of dense, walkable neighbourhoods may benefit from the establishment of urban community gardens, which have been found to confer significant health benefits, including increases in physical activity (Litt et al., 2023).

Finally, as expected, higher neighbourhood walkability was positively related to both engagement and frequency of walking for transport. However, while engagement in walking for transport showed beneficial associations with cardiometabolic health, frequency of walking for transport was positively related to LDL cholesterol. Individuals may frequently engage in walking for transport to visit cafés,

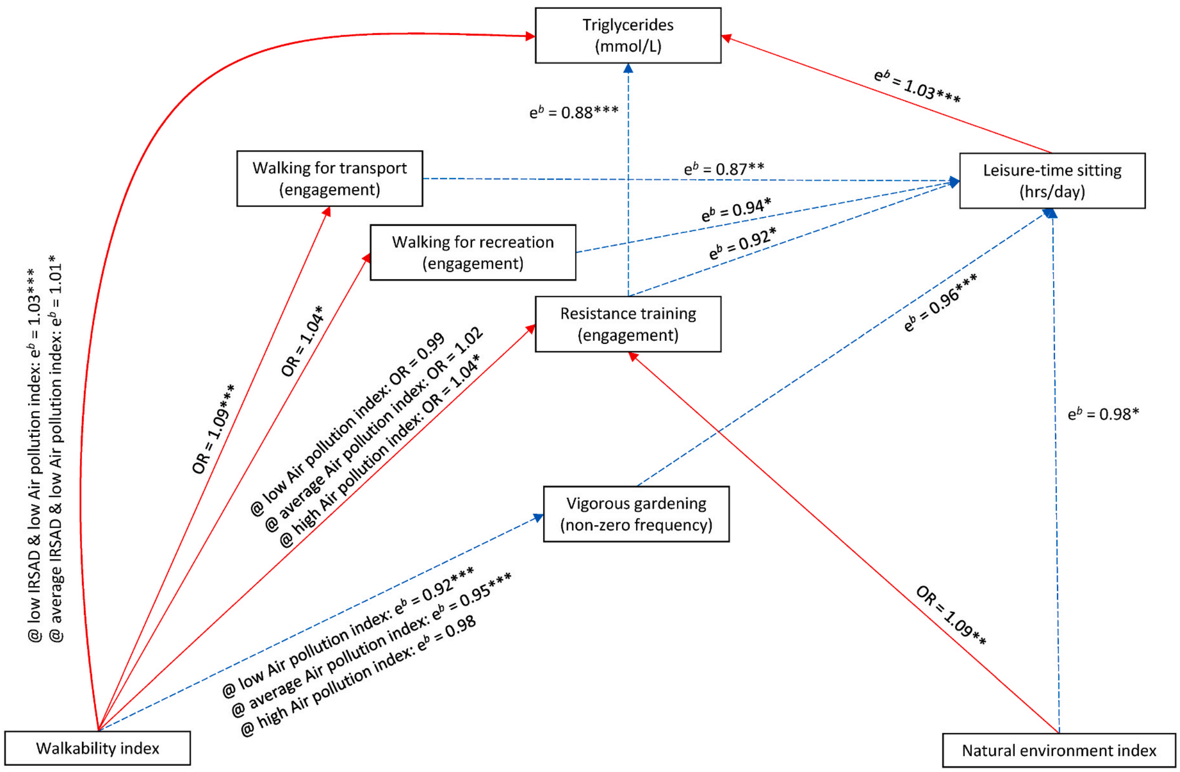

Fig. 5. Direct and indirect (behaviour-mediated) associations of the neighbourhood built and natural environment with triglycerides (mmol/L). Arrows linking variables indicate significant associations. Red full arrows denote positive associations, while blue dashed arrows denote negative associations. @ denote associations moderated by the Air pollution index and, where applicable, the Index of Relative Social Advantage and Disadvantage (IRSAD). For associations moderated by Air pollution index only, estimates of the association are given at different values of the Air pollution index (low = 1 standard deviation below the mean; average = mean; high = 1 standard deviation above the mean). For associations moderated by both IRSAD and Air pollution index, only statistically significant estimates of associations are given for specific values of the two moderators (low = 1 standard deviation below the mean; average = mean). OR = odds ratio from models with binomial variance and logit link functions (engagement in walking for different purposes and resistance training); e^b = exponentiated regression coefficient from models with Gamma variance and logarithmic link functions (leisure-time sitting, non-zero frequency of vigorous gardening and triglycerides). *p < .05; **p < .01; ***p < .001. Regression coefficients and their 95% confidence intervals are presented in Tables 4, 5 and S2 (supplementary data). Estimates of path coefficients were obtained using a set of regression models (one for each mediator and cardiometabolic health indicator) rather than simultaneously.

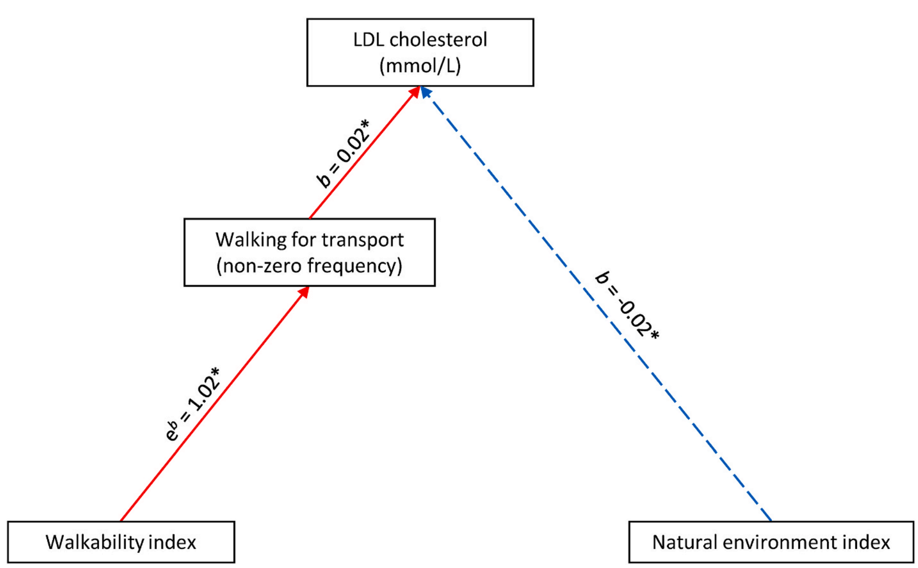

Fig. 6. Direct and indirect (behaviour-mediated) associations of the neighbourhood built and natural environment with LDL cholesterol (mmol/L). Arrows linking variables indicate significant associations. Red full arrows denote positive associations, while blue dashed arrows denote negative associations. *b* = regression coefficient from model with Gaussian variance and identity link functions (LDL cholesterol); e^b = exponentiated regression coefficient from model with Gamma variance and logarithmic link functions (non-zero frequency of walking for transport); *p < .05. Regression coefficients and their 95% confidence intervals are presented in Table 4 and Table S2 (supplementary data). Estimates of path coefficients were obtained using a set of regression models (one for each mediator and cardiometabolic health indicator) rather than simultaneously.

Table 4
Associations of neighbourhood environment attributes with cardiometabolic health indicators: direct main effects models (adjusted for physical activity and sedentary behaviours).

Neighbourhood environment attributes	Waist circumference (cm)	Mean arterial pressure (mmHg)	Glycated haemoglobin (mmol/mol)	HDL cholesterol (mmol/L)	LDL cholesterol (mmol/L)	Triglycerides (mmol/L)
	b (95% CI)	*b* (95% CI)	e^b (95% CI)	e^b (95% CI)	*b* (95% CI)	e^b (95% CI)
Walkability index	−0.081 (−0.320, 0.159)	**0.435 (0.203, 0.666)**	1.002 (0.9996, 1.004)	0.999 (0.995, 1.004)	0.001 (−0.015, 0.013)	1.007 (0.997, 1.017)
Natural environment index	**−0.403 (-0.749, -0.057)**	−0.204 (−0.518, 0.111)	0.999 (0.996, 1.002)	0.994 (0.987, 1.002)	**−0.023 (-0.043, -0.002)**	1.002 (0.989, 1.017)
Neighbourhood IRSAD	**−0.406 (-0.607, -0.206)**	**−0.307 (-0.499, -0.115)**	**1.002 (1.000, 1.004)**	**1.009 (1.005, 1.013)**	0.007 (−0.004, 0.019)	**0.987 (0.979, 0.995)**
Ambient air pollution index	0.370 (−0.002, 0.742)	**−0.580 (-0.930, -0.231)**	**1.004 (1.001, 1.008)**	**0.992 (0.985, 0.999)**	0.002 (−0.020, 0.023)	1.008 (0.994, 1.022)

Abbreviations: IRSAD, Index of Relative Advantage and Disadvantage; *b*, unstandardised regression coefficient from model with Gaussian variance and identity link functions; e^b = exponentiated regression coefficient from models with Gamma variance and logarithmic link functions; CI, confidence intervals. Estimates in bold are significant at a 0.05 two-tailed probability level. All regression coefficients are adjusted for other environmental indices, age, sex, English-speaking background, educational attainment, household income, living arrangements, employment status, work status, neighbourhood self-selection, taking medications relevant to a specific outcome (diabetes, hypertension and/or dyslipidaemia) and physical activity and sedentary behaviour.

Table 5
Associations of neighbourhood physical environment attributes with cardiometabolic health indicators: direct moderating effects of neighbourhood socio-economic status and air quality (adjusted for physical activity and sedentary behaviours).

Moderator	Moderator values	Mean arterial pressure (mmHg)	Triglycerides (mmol/L)	Moderator	Moderator values	HDL cholesterol (mmol/L)
		b (95% CI)	e^b (95% CI)			e^b (95% CI)
Exposure: Walkability index				***Exposure: Natural environment index***		
Neighbourhood IRSAD Air pollution index	M − 1 SD M − 1 SD	**0.845 (0.459, 1.231)**	**1.025 (1.008, 1.042)**	Air pollution index	M − 1 SD	1.004 (0.996, 1.011)
Neighbourhood IRSAD Air pollution index	M − 1 SD M	**0.436 (0.125, 0.747)**	1.008 (0.995, 1.022)	Air pollution index	M	0.994 (0.987, 1.001)
Neighbourhood IRSAD Air pollution index	M − 1 SD M + 1 SD	0.027 (−0.343, 0.398)	0.992 (0.976, 1.009)	Air pollution index	M + 1 SD	**0.985 (0.973, 0.996)**
Neighbourhood IRSAD Air pollution index	M M − 1 SD	**0.655 (0.362, 0.947)**	**1.015 (1.002, 1.028)**			
Neighbourhood IRSAD Air pollution index	M M	**0.435 (0.204, 0.665)**	1.007 (0.997, 1.017)			
Neighbourhood IRSAD Air pollution index	M M + 1 SD	0.215 (−0.025, 0.454)	0.999 (0.989, 1.010)			
Neighbourhood IRSAD Air pollution index	M + 1 SD M − 1 SD	**0.464 (0.050, 0.877)**	1.004 (0.987, 1.022)			
Neighbourhood IRSAD Air pollution index	M + 1 SD M	**0.433 (0.114, 0.752)**	1.006 (0.992, 1.019)			
Neighbourhood IRSAD Air pollution index	M + 1 SD M + 1 SD	**0.402 (0.103, 0.701)**	1.007 (0.994, 1.020)			

Abbreviations: IRSAD, Index of Relative Advantage and Disadvantage; *b*, unstandardised regression coefficient from model with Gaussian variance and identity link functions; e^b = exponentiated regression coefficient from models with Gamma variance and logarithmic link functions; CI, confidence intervals; M, mean; SD, standard deviation. Estimates in bold are significant at a 0.05 two-tailed probability level. All regression coefficients are adjusted for other environmental indices, age, sex, English-speaking background, educational attainment, household income, living arrangements, employment status, work status, neighbourhood self-selection, taking medications relevant to a specific outcome (diabetes, hypertension and/or dyslipidaemia) and physical activity and sedentary behaviours.

restaurants or fast-food outlets. In fact, a travel survey conducted in Australia reported that people walked for almost 67% of short trips to bars, pubs, cafés and restaurants (Eady and Burtt, 2019). Eating out more frequently rather than preparing food at home is usually associated with higher energy and fat intake (Lachat et al., 2012) and, consequently, worse cardiometabolic health (Nago et al., 2014). Interventions and policies aimed at making healthy choices more available in food-serving premises may mitigate this problem.

4.2. Neighbourhood natural environment

Access to green space is deemed to contribute to better cardiometabolic health by reducing residents' exposure to air pollution and noise, exerting a cooling effect on the environment, facilitating physiological stress recovery, encouraging participation in physical activity and promoting social cohesion (Markevych et al., 2017) which, in turn, can also contribute to stress mitigation (Robinette et al., 2018). Similarly, White and colleagues (White et al., 2020) have postulated that access to blue spaces may mitigate urban heat, reduce stress, promote positive social relations and encourage physical activity, all of which are beneficial to cardiometabolic health.

In our study, the relationships of risk factors for CVD with the neighbourhood natural environment were mostly in the expected direction. Higher scores on the natural environment index, combining information on greenspace (parkland) and blue space, were directly negatively associated with waist circumference and LDL cholesterol, and, when using 1.6 km radius buffers, also negatively associated with MAP. In addition, they were indirectly negatively associated with waist circumference, triglycerides and glycated haemoglobin via higher odds of engagement in resistance training and less leisure-time sitting, and indirectly positively associated with HDL cholesterol via the same behavioural pathways. The fact that many parks (Grigoletto et al., 2021) and beaches (Bliss, 2016) have outdoor fitness equipment and many personal trainers run classes in parks may explain the association between the natural environment and resistance training. Residents spending more time outdoors exercising, socialising or relaxing if they have access to nature in the local area (Georgiou et al., 2021; Zhang et al., 2021) may be the reason for them engaging in less leisure-time sitting, which, in this demographic, is mainly represented by TV viewing (Compernolle et al., 2021). Displacing TV viewing with outdoor activities can benefit cardiometabolic health via at least three pathways – higher energy expenditure from non-sedentary activities, less snacking and energy-dense food intake (Pearson and Biddle, 2011) and higher levels of exposure to UV radiation (Gorman et al., 2017).

In general, our findings are consistent with those of previous studies reporting beneficial effects of green and blue spaces on cardiometabolic health (Astell-Burt and Feng, 2020; Dendup et al., 2018; Rahimi-Ardabili et al., 2021), physical activity (Astell-Burt et al., 2014; Georgiou et al., 2021; Van Cauwenberg et al., 2018) and sedentary behaviours (Barnett et al., 2015; Cerin et al., 2020). By supporting an active lifestyle, better access to nature in urban areas appears to lead to better cardiometabolic health. However, in this study, not all associations between the natural environment index and cardiometabolic health were mediated by physical activity and sedentary behaviours. Direct positive effects were observed on waist circumference, LDL cholesterol and HDL cholesterol. Unmeasured leisure-time physical activities (e.g., swimming, surfing, bowling), exposure to UV radiation, which has been associated with reduced risk of obesity and metabolic disease (Gorman et al., 2017), and/or lower stress levels (Catalina-Romero et al., 2013; Sharma et al., 2022; Tomiyama, 2019) resulting from spending time in nature (Zhang et al., 2021) may be responsible for these direct effects.

Finally, we observed a moderating effect of air pollution on the association between the natural environment and HDL cholesterol. A negative direct relationship was found only at above average levels of air pollution, suggesting that time spent outdoors in more polluted areas may have an undesirable effect on HDL cholesterol. It is, though, unclear why this effect was observed only in one of the six examined indicators of cardiometabolic health since previous studies have documented worse metabolic health outcomes for those participating in physical activity in more polluted environments (D'Oliveira et al., 2023).

4.3. Strengths, limitations and future studies

This study addressed several important shortcomings of the research on environmental correlates of cardiometabolic risk factors for CVD. It estimated the independent associations of aspects of the neighbourhood built as well as natural environment with six cardiometabolic risk factors for CVD while adjusting for neighbourhood SES and ambient air pollution. By doing so, unlike most previous studies focusing on one or two dimensions of the urban environment (e.g., air pollution or built environment), it accounted for four key dimensions - built environment, natural environment, air pollution and neighbourhood SES. To better understand how urban design may impact cardiometabolic health across various levels of social and environmental disadvantage, this study also examined the moderating effects of neighbourhood SES and air pollution, and mediating roles of domain-specific physical activity and sedentary behaviours. Such a comprehensive analysis acknowledges the complexities of the real world and the fact that an environmental characteristic may have beneficial as well as detrimental effects on health via different pathways. Methodological strengths include using data from a national study with good geographical coverage and environmental variability, adjustment for neighbourhood self-selection based on self-report measures of reasons for living in a neighbourhood and using directed acyclic graphs to develop analytical models informed by a careful analysis of the relevant literature.

This study has several limitations. The cross-sectional nature of the data limits our ability to prove causal relationships. The natural environment index did not include information on the quality of parkland areas. The land use variables in the walkability index did not distinguish between destinations that are relevant to daily living from those that are not, making it more difficult to distinguish the beneficial from the detrimental effects of dense, walkable neighbourhoods on cardiometabolic health. We lacked traffic-related noise data and, hence, were unable to distinguish the potential effects of noise on cardiometabolic health from those of co-occurring neighbourhood attributes (e.g., traffic-related air pollution and population density). The participants included in the third wave of AusDiab were healthier than those at baseline. Behaviours were assessed using self-reports which are known to have relatively large measurement errors. Information on the usual settings of the physical activity and sedentary behaviours was not available. A substantial proportion of these behaviours may have been undertaken outside the neighbourhood. Data on the length of residence in a particular neighbourhood were not available. These methodological issues may have resulted in an underestimation of the associations.

Future studies would need to determine how aspects of the neighbourhood environment are related to trajectories of cardiometabolic risk factors for CVD across time. While the built and natural environments do not typically change substantially in 5–10 years (the duration of most cohort studies), there is a need for more evidence from longitudinal and quasi-experimental studies that investigate potential effects of the environment on cardiometabolic health and related behaviours. Measures of environmental exposures should encompass all key environmental attributes defining urban environment that may have contrasting direct and behaviour-mediated effects on cardiometabolic health. These encompass density, street connectivity, destinations of daily living that impact physical activity and dietary behaviours, green and blue spaces, air pollution, noise and area-level SES. Failure to include all these factors is likely to result in contradictory, counterintuitive or misleading findings. To accurately estimate the effects of the neighbourhood environment on health, it is important to know how much time individuals spend outdoors and indoors in their local community. Future studies should collect information on activity spaces using devices (e.g., global positioning system monitors or ecological momentary assessment surveys) or map-based interviews (Kestens et al., 2018).

5. Conclusion

Within a relatively low-density and low-pollution context such as that of urban Australia, denser, walkable neighbourhoods with good access to nature may benefit residents' cardiometabolic health by facilitating walking for transport and leisure-time physical activity, reducing the need for transport-related sitting (motorised transport), and displacing some indoor leisure-time sitting with more active outdoor pursuits. Possible downsides of living in denser neighbourhoods are having limited opportunities for gardening-related physical activities, exposure to higher levels of noise and air pollution, and exposure to eating-out outlets leading to less healthy dietary patterns with adverse effect on cardiovascular health. Although, within the setting of this study, ambient air pollution measures appeared to act as proxies for traffic-attracting destinations of daily living supporting an active lifestyle, our findings suggest that time spent in public open spaces with higher level of air pollution may be associated with less favourable cardiometabolic outcomes (e.g., lower HDL cholesterol) than time spent in less polluted locations. Finally, all the above-mentioned findings were generally similar across levels of neighbourhood advantage and disadvantage, although, in a few instances, residents of more disadvantaged neighbourhoods displayed stronger associations indicating that they may be more vulnerable to harmful environmental exposures compared to their more advantaged counterparts. Therefore, socially disadvantaged neighbourhoods should be prioritised in environmental public health interventions aimed at enhancing residents' cardiovascular health.

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Ethical statement

The AusDiab study was approved by the Alfred Hospital Ethics Committee (ref. no. 39/11) and conducted according to the guidelines of the Declaration of Helsinki. All participants provided written consent prior to partaking in the study.

CRediT authorship contribution statement

Ester Cerin: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Yih-kai Chan:** Project administration, Supervision, Resources, Writing – review & editing. **Mark Symmons:** Resources, Writing – review & editing. **Maria Soloveva:** Resources, Writing – review & editing. **Erika Martino:** Data curation, Investigation, Software, Writing – review & editing. **Jonathan E. Shaw:** Conceptualization, Data curation, Funding acquisition, Investigation, Resources, Writing – review & editing. **Luke D. Knibbs:** Data curation, Methodology, Resources, Software, Writing – review & editing. **Bin Jalaludin:** Funding acquisition, Writing – review & editing. **Anthony Barnett:** Conceptualization, Funding acquisition, Validation, Writing – review & editing.

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

Data will be made available on request.

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Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2023.117524.

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