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Shifting car travel to active modes to improve population health and achieve transport goals: A simulation study

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ABSTRACT

Introduction: Being physically active has multiple health benefits and contributes to the reduction of co-morbidities and mortality from chronic diseases. Active transport (walking and cycling) contributes to population health by enabling physical activity. We developed a simulation model to measure health impacts of transport scenarios for Melbourne, Australia. Our aim was to demonstrate active transport health impacts and support the materialization of policies for healthy cities and people. The model measures health impacts of increased physical activity from replacing short car trips for any purpose or for commuting under 5 km by walking and cycling.
Methods: We developed a micro-simulation model of physical activity and disease risk in combination with the well-established proportional multi-state life table model. We quantified life course health including health adjusted-life years, life years, new cases of diseases prevented, and deaths prevented for 14 chronic diseases associated with physical inactivity for the adult population of people from Melbourne, Australia in 2017.
Results: Over the life course of the Melbourne adult population of 3.6 million people in 2017, gains in health-adjusted life years ranged from 5,100 (95% Uncertainty Interval (UI) 3,700 to 6,500) for the scenario replacing commute trips by car under 1 km with walking up to 738,800 (95% UI 546,000 to 935,000) when replacing car trips under 2 km with walking and between 2 km and 5 km with cycling. We also estimated benefits in terms of reductions of new cases of diseases and deaths prevented, with the greatest gains for ischemic heart disease, stroke, Alzheimer's and other dementias and type 2 diabetes.
Conclusions: We found that shifting car travel to active modes would accrue important health benefits for the 2017 Melbourne population. Our results support policies and strategies for sustainable transport planning to contribute to reduce the burden from chronic diseases and environmental impact of car-oriented cities.

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1. Introduction

Being physically active has multiple health benefits, including preventing and managing cancers, cardiovascular diseases, type 2 diabetes and mental health diseases and contributing to reduced co-morbidities, mortality and burden of disease (Blondell et al., 2014; Kyu et al., 2016; World Health Organization, 2020). Specifically, physically active people have a 19% lower risk of all-cause mortality in comparison to inactive people (Woodcock et al., 2011). To maintain good health and prevent diseases, the World Health Organization recommends adults aged 18 to 65 do at least 150 min of moderate physical activity or 75 min of vigorous physical activity, or a combination of both per week. However, in 2016 worldwide, only 28% of adults manage to achieve these physical activity recommendations with high income Western countries amongst the most physically inactive (43%). In Australia, half of the adult population is physically inactive (Australian Institute of Health Welfare, 2019; Guthold et al., 2018) with this contributing to 20% of mortality and morbidity from diabetes, some types of cancer (bowel, uterine, breast), dementia and cardiovascular diseases (Australian Institute of Health Welfare, 2019).

To improve population levels of physical activity, multilevel and multisector interventions and policies targeting both individuals and the environments where people live, learn, work, play and study are required (Reis et al., 2016; Sallis et al., 2006). This is aligned to the built environment as a key social determinant of health that is heavily influenced by city planning and infrastructure development. Interventions aimed at changing the built environment have the potential to cause long term and sustained change in physical activity and health. For example, physical activity benefits have been demonstrated in natural experiments of city planning and transport interventions aimed at increasing walking and cycling (Aldred et al., 2021; Smith et al., 2017). In addition, health simulation studies have found population level health benefits from increased physical activity outweigh the health risks from exposure to air pollution and road injuries when shifting private car travel to active modes (Mueller et al., 2015). Active travel also contributes to reductions in congestion and greenhouse gas emissions. For example, empirical evidence from Washington DC showed decreased congestion of 4% attributable to the implementation of a bike sharing scheme (Hamilton and Wichman, 2018). A longitudinal study of seven European cities found an approximate reduction in carbon dioxide emission of 0.5 tonnes per year per person when replacing car trips with cycling (Brand et al., 2021).

In order to deliver liveable and environmentally sustainable cities, the Australian government endorses the use of city planning and improvements to transport systems to support active transport (Commonwealth of Australia, 2016). In 2017, the Victorian State Government in Australia published “Plan Melbourne 2017–2050”, the long-term strategic plan for the Melbourne metropolitan region. Plan Melbourne and the Precinct Structure Planning Guidelines for greenfield developments (Victoria Planning Authority, 2021) address a range of challenges relating to transportation and infrastructure. One of the key aims of these strategies is to increase walking, cycling and use of public transport and to decrease the reliance on private motor vehicles through the planning and delivery of supportive infrastructure such as cycle ways and increased public transport (State Goverment of Victoria, 2017). Additionally, Plan Melbourne is based on the hallmark of a 20-min neighbourhood, recognized globally to create local town/activity centers where people can access everyday needs within a 20-min return walk (City of Portland, 2022; Gilbert and Woodcock, 2022).

However, in Melbourne, private car travel is the dominant mode of transport (Australia Bureau of Statistics, 2017) despite the support of government policies and strategies to encourage active transport. Reasons for this lie in Melbourne’s low density sprawling urban footprint, transport preferences, and continued funding priority for private vehicle usage (Pojani et al., 2018). A shift from private car travel to active modes (walking and cycling) needs to be prioritised and will contribute to reduce the health burden from physical inactivity.

The capital city of Melbourne in the state of Victoria is the 2nd most populous city of Australia and 49% of its residents do not meet recommended physical activity guidelines (Victorian Agency for Health Information, 2021). In addition, prevalence of chronic diseases and multi-morbidities is high: 7% of the adult population reported being diagnosed with heart diseases; 7% with some type of cancer; 6% with type 2 diabetes; and 19% with more than one condition (Victorian Agency for Health Information, 2021). Past research has highlighted the need for quantifiable evidence to assistant and advocate for the implementation of evidence-based decision-making in public health (Hooper et al., 2019). Internationally, tools, models and frameworks are being developed to generate quantitative evidence for the health and environmental impacts of active transport. For example, the Health Economic Assessment Tool (World Health Organization, 2017) and the Integrated Transport and Health Impacts Model (ITHIM-R) suite of tools and code (Abbas and Woodcock, 2020). Australia currently lacks publicly available tools and methods that quantify the health impacts of transportation. Consequently, we developed the first open-source simulation model in Australia that quantifies the health impacts of active transport scenarios for Melbourne. The assessments were based on increased physical activity due to replacing short car trips under 5 km by walking and cycling in Melbourne, aligned with a walkable and cycleable distance relating to 20-min neighbourhoods (State Goverment of Victoria, 2017). The model was developed as part of a larger research partnership project with the Victorian Department of Transport (DoT) sharing research evidence with policy and planning practitioners.

2. Methods

2.1. Study area

Greater Melbourne (hereafter referred to as Melbourne) is the capital of the south-eastern state of Victoria, Australia and the second largest city in Australia (Australian Bureau of Statistics, 2016). According to population projections, Melbourne is predicted to grow from 5.1 million in 2021 to 8.6 million people by 2066 (Centre for Population, 2020; State Goverment of Victoria, 2017). By 2031, Melbourne will be the largest capital city in Australia, overtaking Sydney. The Australian population, including Melbourne, is also projected to continue to age, with the median age increasing from 37 to 40 years old.

2.2. Overview

The modelling framework is depicted in Fig. 1 and includes three main sections: 1) Scenarios; 2) Micro-simulation; and 3) Macro-simulation.

The scenarios calculate the time travelled for each trip-stage where short trip-stages are replaced with walking, cycling or a combination of both. A trip is defined as a one-way movement from an origin to a destination for a single purpose, but possibly, by multiple modes (Eady and Burtt, 2019). A stage is defined as a one-way travel movement and a new stage defined when there is a change in transport mode (Department of Transport, 2020). For example, a trip with origin at home and destination work might include walking from home to the station (stage 1), train ride (stage 2) and walking from train station to work (stage 3).

The micro-simulation calculated the impact of changes in physical activity on the risk of developing chronic diseases due to the increase in either walking, cycling or a combination of both (that occurs when short car trips are replaced by these modes). The increase in physical activity reduces disease risk at the individual level which is captured by the potential impact fraction (PIF).

The macro-simulation modelled 5-year age groups and sex cohorts using a proportional multi-state life-table (PMSLT) (Barendregt et al., 1998; Cobiac et al., 2009) The PMSLT included diseases' processes and a life table for the Melbourne population in 2017. We modelled a PMSLT for the base case and for each of the scenarios in one-year cycles until everyone died or reached the age of 100. The diseases' processes in the scenarios were modified by the PIF to reflect the impact on diseases from changes in physical activity. The health outputs were measured as the difference between the diseases' processes and life tables for the base case and scenario respectively and included new cases of chronic diseases and mortality prevented for the modelled diseases, health-adjusted life years (HALYs) and life years gained. HALYs represent life years adjusted for a reduction in the quality of life attributable to disability of diseases and injuries (Gold et al., 2002).

The macro-simulation in combination with the PIF for physical activity was originally developed for the Assessing the Cost-Effectiveness in Prevention project (ACE-prevention) (Cobiac et al., 2009). For the model that we used for this paper we made significant updates and upgrades to modelling physical activity (micro-simulation) at the individual level; and, for updating relative risks for physical activity for the 14 modelled chronic diseases.

The model in this paper builds up on the THAT-Melbourne (https://auo.org.au/transport-health-assessment/) which partially builds upon the ITHIM-Global model (https://github.com/ITHIM/ITHIM-R/tree/master**) and it is implemented in the R programming language for statistical computing (R Core Team, 2022)** and used a range of R packages (Corporation and Weston, 2022; Dowle and Srinivasan, 2023; Ellis and Schneider, 2023; Garcia et al., 2023; Kuhn, 2022; Wickham et al., 2019).

Data sources and further methodological details are explained in the sections that follow.

2.2.1. Scenarios

We used travel survey data from the Victorian Integrated Survey of Travel and Activity (VISTA) collated throughout 2017-18 for Greater Melbourne and Geelong (Transport for Victoria, 2017). Randomly selected households were asked to complete a household form with each adult required to complete a travel diary for a single specified day (with an adult completing the survey for children). The survey aims to capture average travel behaviour for day-to-day travel on weekday and weekend for trips including going to and from work, going shopping, visiting friends, and going to sporting events, among other trip purposes. The travel diary asked respondents about travel and activities on a travel day. The Greater Melbourne travel survey included 23,166 trips. Travel data were

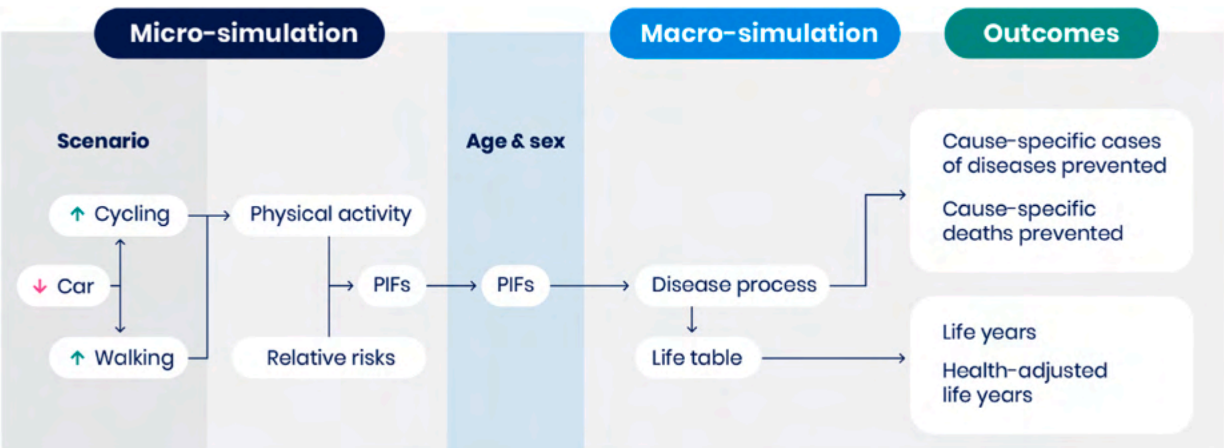

Fig. 1. Model analytical framework.
Note: PIF = potential impact fraction.

collected for all individuals in each household aged above 5. We limited the analysis to individuals aged over 16, which is the legal age to drive a car with a Learners Permit in Victoria, leaving 19,552 trips and 23,218 trips stages for analysis.

We modelled a variety of scenarios combining trip purposes (All and Commuting respectively) with private car travel distances replaced by walking and/or cycling (Table 1). Car includes travel by private motor vehicle as driver or passenger and as passenger in a taxi.

The distances for replacing car trips with walking are aligned with the 20-min neighbourhood concept (State Goverment of Victoria, 2017) and within 800 m, which is a distance found to be associated with walking trips (Gunn et al., 2017). Our chosen distances for cycling are supported by past research for mode share of cycling in 6 continents and 17 countries where cycling trips were most commonly under 5 km (Goel et al., 2021).

Based on the VISTA survey we created a trip file for each of the scenarios (n = 14), which contained base case (representing no change in transport mode) and scenario mode of travel for each trip stage along with base case time and distance and scenario time. We derived scenario time from the base case stage distance from car trips divided by speed for the replacing mode, being either walking or cycling. The median speed across the VISTA sample was 4 km/h for walking and 11 km/h for cycling. Base case and scenario time for walking and cycling were then used in the micro-simulation as explained in the next section.

2.2.2. Micro-simulation

The micro-simulation is based on the persons file of the VISTA survey and the National Health Survey (NHS). The VISTA survey collected information on the individuals completing the survey, including their age and sex. The VISTA persons file included 9,036 people, and after removing individuals aged under 16 years old a working file of 7,117 persons remained. The NHS is a representative sample of Australian adults (aged 15 and above). The data were collected by the Australian Bureau of Statistics and published as the National Health Survey, 2017–18. A sample of 21,315 adults was available. NHS survey respondents were asked about the time they spent doing exercise (for leisure or walking for transport) and workplace physical activity in the last week (see Table A1 in the supplementary material for NHS variables).

We created a matched population of individuals (Garcia et al., 2021) by randomly appending leisure time physical activity from the NHS to the VISTA persons file (see supplementary material Section 1). This process was conducted to compute the total level of energy expenditures based on marginal metabolic of task per hour (mMET-hours) per week for each individual in the VISTA persons file. Marginal METs only consider energy expended above resting metabolic rate. We computed individual mMET-hours from time spent walking and cycling for transport (VISTA survey) and time spent doing leisure moderate physical activity, leisure vigorous physical activity and walking for leisure (NHS) in one week by their corresponding mMET-hours scores (see Table A2 in the supplementary material). The VISTA data is for one day; hence, we derived weekly data for walking and cycling for transport by multiplying by 7. For each of the scenarios, each of the individuals in the matched population had a base case and a scenario level of mMET-hours per week. Scenario mMET-hours included changes in time spent walking and cycling for transportation resulting from replacing private car trips by these modes.

Based on the latest evidence for the dose response relationship between physical activity and diseases we modelled fourteen diseases including: Alzheimers disease and other dementias, ischemic heart disease, stroke, diabetes mellitus type 2, colon cancer, lung cancer, head and neck cancer, liver cancer, stomach cancer, chronic myeloid leukemia, multiple myeloma, depression and for females only: breast and uterine cancers (Garcia et al., 2023; Pearce et al., 2022). Each individual in the matched population had an associated relative risk for developing each of the above diseases that corresponded to the base case and scenario mMET-hours which were inputs for the potential impact fraction (PIF) (Barendregt and Veerman, 2010) calculations (Equation 1).

$$PIF_{disease} = \frac{RR_{baseline} - RR_{scenario}}{RR_{baseline}}$$

Table 1
Scenarios.

Scenarios		
Trip purpose		
	All: *Work related, education, leisure, shopping, pick-up or drop-off someone/something, personal business, other, accompany someone, education, at or go home*	
	Commuting: *Work related and education*	
Replace car trips with		*Scenario name*
	Walking for trips under 1 km	1 km ≥ walking
	Walking for trips under 2 km	2 km ≥ walking
	Cycling for trips under 2 km	2 km ≥ cycling
	Cycling for trips under 5 km	5 km ≥ cycling
	Walking for trips under 1 km and cycling for trips greater than 1 km and shorter than 2 kms.	walking ≤ 1 km; 1 km < cycling ≤ 2 km
	Walking for trips under 1 km and cycling for trips greater than 1 km and shorter than 5 kms.	walking ≤ 1 km; 1 km < cycling ≤ 5 km
	Walking for trips under 2 kms and cycling for trips greater than 2 kms and shorter than 5 kms.	walking ≤ 2 km; 2 km < cycling ≤ 5 km

Table 2
Proportion of the population meeting physical activity guidelines time recommendation for modelled scenarios.

Scenario	All trips	Commute trips
Walking $\leq$ 1 km	55%	54%
Walking $\leq$ 2 km	60%	54%
Cycling $\leq$ 2 km	59%	54%
Cycling $\leq$ 5 km	68%	56%
Walking $\leq$ 1 km; 1 km $<$ Cycling $\leq$ 2 km	60%	54%
Walking $\leq$ 1 km; 1 km $<$ Cycling $\leq$ 5 km	69%	56%
Walking $\leq$ 2 km; 2 km $<$ Cycling $\leq$ 5 km	69%	56%

Equation 1: PIFs calculations for individuals

To transition from the micro-simulation to the macro-simulation we calculated average PIFs by age and sex groups using VISTA data persons' weights to adjust for unequal probabilities of selection into the sample. PIFs by age and sex where then used to estimate the effect of changes in physical activity on the risk of included diseases. We refer to this as the disease process in the macro-simulation model.

For the matched population we also estimated the contribution of transport related walking and cycling for each of the scenarios towards achieving the Australian Physical Activity Guidelines time component described as follows (Australian Goverment Department of Health, 2021): for adults (18–64 years) 2.5–5 h of moderate activity or 1.25–2.5 h of vigorous activity or a combination of both is recommended. For older adults (65 years and over), at least 30 min of moderate activity, preferably on most days is recommended.

2.3. Macro-simulation model

The PMSLT consists of a disease process for each of the included diseases and a life table which are modelled for both the base case and scenario for the Melbourne adult population alive in 2017 in 5-year age cohorts and by sex. The health outputs are calculated as the cumulative difference, over the lifespan of the modelled cohorts, between the disease processes and life tables for the base case and scenario, respectively. The difference between the base case and chosen scenario starts with a change in diseases' incidence initiated by the PIF in the scenario diseases' processes which in turn modifies disease prevalence and mortality. The life table all-cause mortality and all-cause years lived with disability capture changes in the prevalence and mortality of diseases, which, in turn, affect life years and health-adjusted life years (HALYs). The decrease in incidence and mortality of the modelled diseases has a positive impact on the lifespan of the modelled cohorts. This, in turn, results in an increase in the number of both explicitly and implicitly modelled diseases as the cohorts age. Implicit diseases are captured by all-cause mortality and all-cause years lived with disability. The population cohorts within the macro-simulation are modelled until everyone dies or reaches the age of 100, that is to say, any survivor at the age of 100 has a risk of dying from all causes of 1. The PMSLT has a cohort perspective (Blakely et al., 2020) and to reflect on this in our modelling we used forecasts for all-cause mortality and for diseases' incidence and case fatality. This means, for example, that a female aged 22 years old in the baseline year of 2017 faces an all-cause mortality rate at age 65 as per the projected all-cause mortality rate for a female aged 65 in 2060 (Supplementary material tables A5). Future projections for incidence and case fatality were derived using published age standardized trends or derived from past data when future trends were not available (See supplementary material table A7). Health outcomes are presented in terms of the benefits for actual starting population cohorts, which can be found in Annex Table A8, as well as starting cohorts of 100,000 people.

The model assumes that diseases are independent from one another (i.e. the probability of developing one disease is unrelated to the probability of developing another) and are independent from all causes of death (Barendregt et al., 1998). Supplementary material Section 2 provides further details on the PMSLT including data inputs.

2.4. Probabilistic sensitivity analysis

We performed a probabilistic sensitivity analysis (Briggs et al., 2006) for all outcome measures by Monte Carlo simulation (1,000 iterations) and reported the 50th percentile, and intervals for the 2.5 and 97.5 percentiles of the simulation results. These intervals indicate the degree of uncertainty for the parameters estimated in the model given the uncertainty for the relative risks for physical activity diseases and the relative risks for diabetes and cardiovascular diseases. For the physical activity relative risks we followed the methods developed for the ITHIM-R models (Abbas and Woodcock, 2020; Garcia et al., 2021) and for diabetes see supplementary material Section 2.1.

In brief, for physical activity we sampled a single uniform variable and selected the same quantile for each modelled individual (micro-simulation). In this way, the same relative risk distribution was used to derive base case and scenario relative risks. This method ensures a unique distribution for relative risks for each Monte Carlo run. Relative risks for each individual were then defined by mapping the quantile and the truncated normal distribution (0,1) defined by the mean and upper and lower bounds for the corresponding relative risk for the given mMET hours (Abbas and Woodcock, 2020; Garcia et al., 2021). Relative risks for diabetes were used in the macro-model and were defined using the lognormal distribution.

2.5. Assumptions

The PMSLT models the future health trajectories of age and sex cohorts. Trends were applied to the diseases' incidence and case fatality for the 14 diseases and all-cause mortality to reflect future changes (see Table A7 in the supplementary material). However, trends were not applied to the physical activity components within the model as derived from the NHS and VISTA survey data. This implies that we assumed that the reported physical activity and travel patterns in 2017-18 also prevail in the future. For example, those in the age cohort 20–24 in 2017 (simulation baseline) will have the physical activity and travel patterns observed of those aged 25–29 years of age in 2017 when they reach the age of 25-29 (by sex) within the simulation.

2.6. Data availability and code

We developed and implemented the model in the statistical computing software R (https://github.com/healthy-liveable-cities/that-melbourne). Processed data is available in the repository for running the model and all data sources are listed in the Supplementary Material. We produce results for 14 scenarios, by age and sex groups, with selected results presented in this paper in the next section. For a visualization of the complete results see here (https://belenzapata-diomedi.shinyapps.io/presentation_dashboard_MD) and for the data supporting the visualization see here (https://doi.org/10.25439/rmt.22306432).

3. Results

3.1. Base case

For the base case, representing no changes in transport mode share, 63% of trip-stages were by car, 27% walking, 8% by public transport, 1% cycling and the 1% by other modes. Fig. 2 highlights that cars are commonly used for short trip stages, with 15% of trip stages under 1 km and 52% of trip stages between 1 and 2 km being completed using cars, regardless of trip type. However, for commute trips, cars are used less frequently for short distances. Specifically, only 7% of trips under 1 km and 34% of trips between 1 and 2 km are completed by car. While commute trips make up 29% of all trips, the lower proportion of short trips taken by car for commuting purposes suggests that replacing these trips alone would lead to significantly lower impacts on physical activity and health.

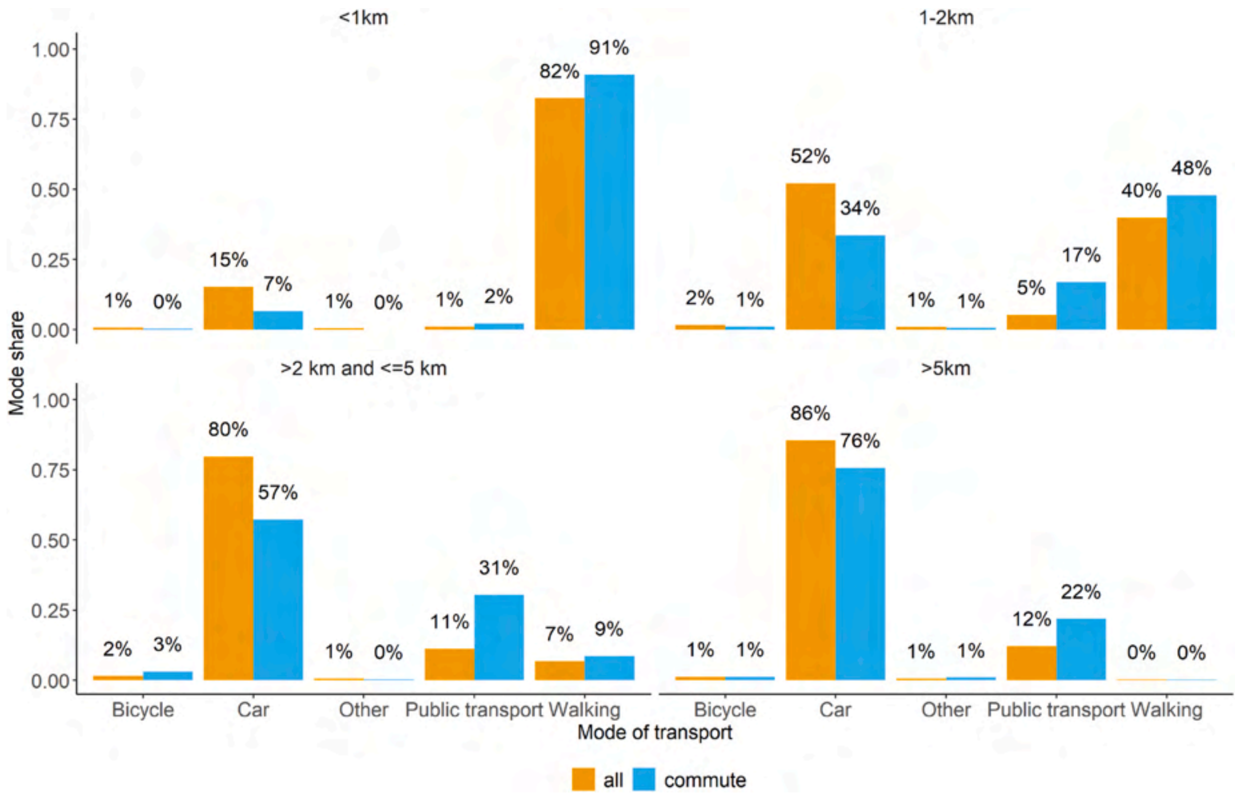

Fig. 2. Transport mode share for trip stages by distance category
Note: Public transport includes train, public bus, school bus and tram. Other includes motorcycle and other forms of transport not specified in the survey.

As the population ages, their proportion of commute trips decreases for both females and males. For females, however, the proportion of commute trips over all trips is lower than male commute trips for all age groups (Fig. 3).

3.2. Scenarios

We calculated changes in transport mode share for 14 scenarios based on trip purposes (All or Commute) and distances replaced by walking, cycling or a combination of both (see Table 1). The scenario results were summarised by the total population and by sex (females and males) and age groups (16–19, 20–39, 40–65 and 65 plus years old). In Fig. 4 we present base case and scenario mode share for the 14 scenarios, for all age groups and all sexes combined separately by trip purposes (Commute and All). The greatest gains in terms of reducing car mode share is observed for the scenarios where car trips less than 5 km are replaced with cycling; less than 1 km with walking and between 1 km and 5 km with cycling; and less than 2 km with walking and between 2 km and 5 km are replaced with cycling for all trip types.

3.3. Physical acivity guidelines

For the base case, 53% of all adults (aged 18–64, and over 65) met the recommended guidelines. Table 2 presents results of the proportion of the adult population that meet physical activity guidelines for each of our modelled scenarios. The greatest improvements to achieving the physical activity guidelines came from two scenarios. The first scenario replaced all trip types by car under 1 km with walking and replaced all trip types by car between 1 and 5 km with cycling. The second scenario replaced all trip types by car under 2 km with walking and replaced all trip types by car between 2 and 5 km with cycling. Differences amongst males and females are negligible, and hence are not reported here.

3.4. Health outcomes

Table 3 shows that over the life course of the Melbourne adult population of 3.6 million people in 2017, gains in health-adjusted life years (HALYs) ranged from 5,098 (95% Uncertainty Interval (UI) 3,733 to 6,488) for the scenario replacing commute trips by car under 1 km with walking up to 738,783 (95% UI 546,248 to 935,064) when replacing car trips under 2 km with walking and between 2 km and 5 km with cycling (Table 4). For these same scenarios, gains in life years ranged from 4,000 (95% UI 2,905 to 5,104) to 587,968 (95% UI 432,113to 745,709). HALYs gained are higher than life years suggesting that shifts from car travel to active modes extends life for the modelled population and increases their quality of life. This is because HALYs adjust life years by disability, with our results indicating an overall decrease in disability from diseases included in the modelled population. Gains are nearly evenly distributed amongst females (1.9 million people) and males (1.7 million people), however, there are important differences in gains when comparing age groups (Fig. 5).

For comparison purposes in Fig. 5 we present gains in HALYs and life years per 100,000 population for females and males

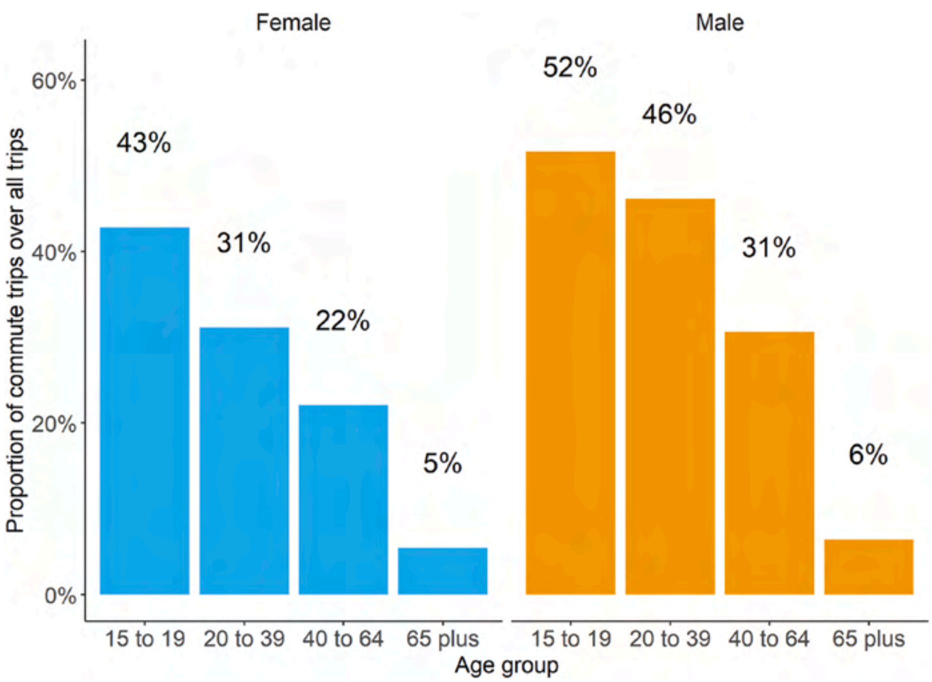

Fig. 3. Proportion of commute trips in VISTA survey by age group and sex.

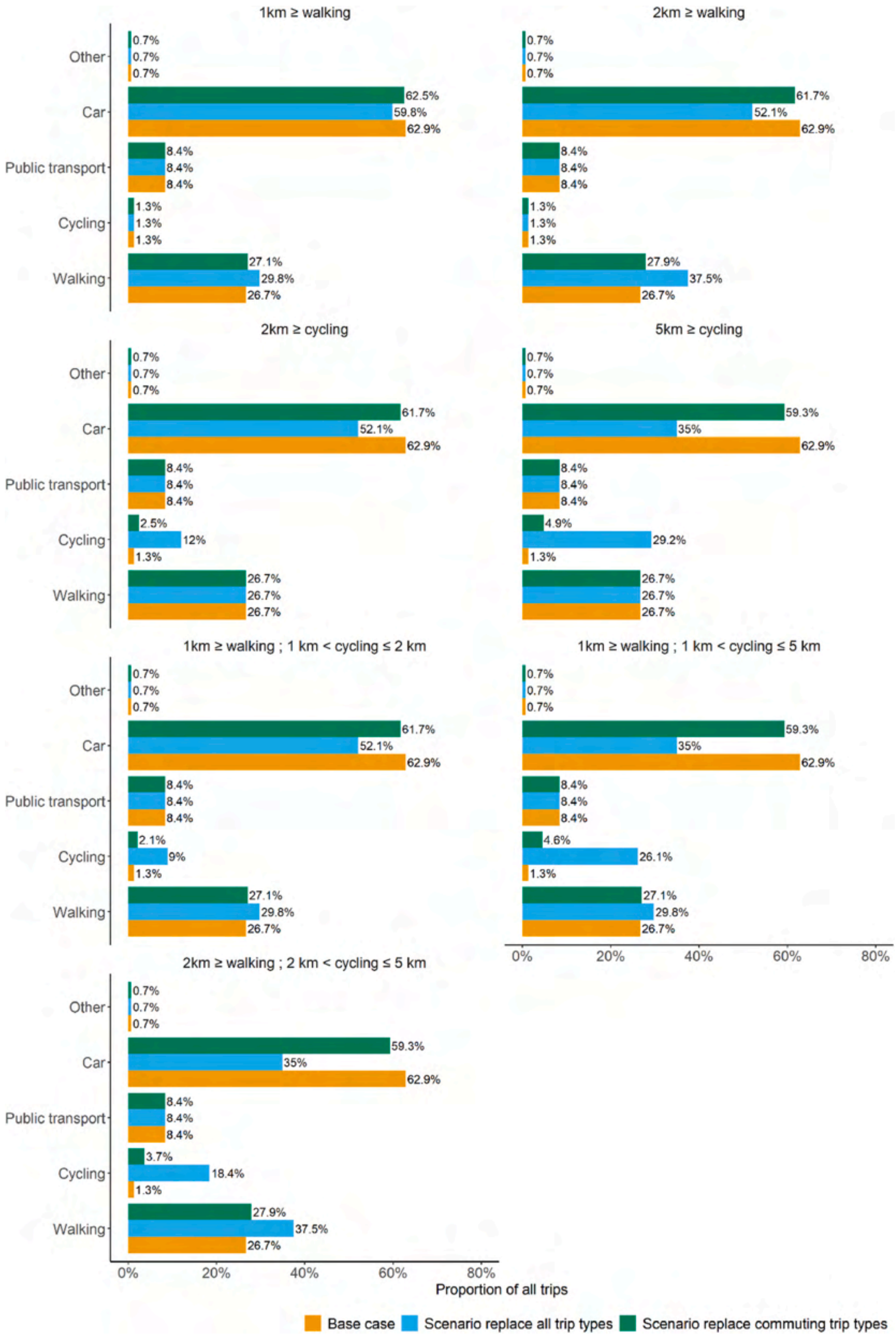

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Fig. 4. Transport mode share for the base case and scenarios.

separately by age groups for two selected scenarios: replacing car trips under 2 km with walking and between 2 km and 5 km with cycling for all trip types and the same distances but for commute trips only. As observed in the graph, gains per 100,000 population for HALYs and life years decrease with increasing age for both males and females, and more notably for the scenario including commute trips only. This is explained by two reasons. First, modelled individuals increase their physical activity attributable to the modelled scenarios for the rest of their lives, with an individual in the age group 15–19 years old accumulating health benefits over more years compared to an individual in the age group 65 plus years old. Second, on average, younger people do more commute trips in comparison to older people (Fig. 3) which explains that the difference among age groups is higher when evaluating commute trips only.

Over the life course of the simulated population, the greatest gains in both HALYs and life years are in the future between years 30 and 55 of the simulation (see supplementary material Section 3). Gains for both outcomes peak between years 50 and 55. Our results support existing evidence that chronic diseases occur in the older populations, reinforcing the importance of early prevention.

3.5. Diseases

For each scenario, we estimated a reduction in the number of new cases (incidence) for all the modelled diseases, with the greatest gains observed for type 2 diabetes, ischemic heart disease, Alzheimer's disease and other dementias (Table 4). We estimated the highest reduction in incidence of diseases for replacing car trips under 2 km with walking; and replacing car trips between 2 km and 5 km with cycling for all trip types. For this scenario, we estimated a reduction in incidence of 36,992 (95% UI 29,988 to 44,169) for type 2 diabetes, 34,544 (95% UI 29,827 to 39,407)) for ischemic heart disease, 23,400 (95% UI 14,307 to 32,592) for Alzheimer's disease and other dementias and 21,498 (95% UI 18,566 to 24,519) for stroke over the life course of the Melbourne population. Results were more modest for the scenarios replacing commuting trips only. Notably, the reductions in new cases of disease for Alzheimer's disease and other dementias are considerably lower when only commute trips are included. This is aligned with the fact that this disease onset is in older age groups and only 6% of those aged 65 or more commuted (Fig. 3).

We estimated the greatest reductions in deaths for ischemic heart disease with 17,022 (95% UI 15,185 to 19,010), for Alzheimers disease and other dementias 13,992 (95% UI 8,406 to 19,672) and stroke 5,262 (95% UI 4,841 to 5,710) for the scenario replacing car trips under 2 km with walking and replacing car trips between 2 km and 5 km with cycling for all trip types. Likewise with new cases of diseases prevented. Deaths prevented are considerably lower when only simulating commute trips (Table 5).

In Figs. 6 and 7 we present new cases of diseases and deaths prevented for the modelled diseases per 100,000 population for females and males separately by age groups. Prevented deaths are limited to the diseases explicitly modelled. If a person in a cohort does not die from one of these diseases, they still face a risk of mortality from other modelled disease and from general all-cause mortality. For presentation purposes we selected the scenarios and diseases with the most gains. Notably, new cases of diseases prevented per 100,000 population for Alzheimer's disease and other dementias are higher for older age groups as opposed to younger and in younger age groups for males the number of diseases increased. This is explained by the high incidence rate of Alzheimer's disease and other dementias in older age groups in comparison to other modelled diseases and the modelled scenarios extending life. Therefore, younger age groups live longer and develop diseases later in life that would not be developed if life was not extended. Similar results for Alzheimer's disease and other dementias are observed for deaths prevented (Fig. 7).

Table 3
Health-adjusted life years and life years over the life course of the Melbourne adult population (95% uncertainty interval).

Scenario	Health-adjusted life years (thousand)			Life years (thousand)		
	Total	Females	Males	Total	Females	Males
All trips						
Walking ≤ 1 km	112 (81–143)	61 (44–78)	51 (37–65)	94 (68–121)	51 (37–66)	43 (31–55)
Walking ≤ 2 km	400 (293–507)	190 (139–242)	210 (154–266)	328 (240–416)	151 (110–152)	177 (131–224)
Cycling ≤ 2 km	382 (279–485)	182 (132–232)	200 (147–254)	314 (229–399)	144 (105–185)	169 (124–215)
Cycling ≤ 5 km	728 (537–921)	348 (256–442)	379 (281–480)	579 (425–735)	268 (195–341)	311 (230–394)
Walking ≤ 1 km; 1 km < Cycling ≤ 2 km	388 (284–494)	185 (135–236)	203 (149–258)	319 (233–406)	147 (107–188)	172 (126–218)
Walking ≤ 1 km; 1 km < Cycling ≤ 5 km	733 (541–928)	351 (258–445)	382 (283–483)	583 (429–740)	270 (197–344)	313 (232–396)
Walking ≤ 2 km; 2 km < Cycling ≤ 5 km	739 (546–935)	354 (260–449)	385 (286–487)	588 (432–746)	272 (198–347)	316 (234–399)
Commuting trips						
Walking ≤ 1 km	5 (4–6)	1 (0–1)	4 (3–5)	4 (3–5)	1 (0–1)	3 (2–4)
Walking ≤ 2 km	20 (15–25)	11 (8–14)	9 (7–11)	15 (11–19)	8 (6–10)	7 (5–9)
Cycling ≤ 2 km	19 (14–24)	11 (8–13)	8 (6–10)	14 (10–18)	8 (6–10)	6 (5–8)
Cycling ≤ 5 km	49 (37–62)	25 (18–31)	25 (19–31)	35 (26–45)	17 (12–21)	18 (14–23)
Walking ≤ 1 km; 1 km < Cycling ≤ 2 km	19 (14–24)	11 (8–13)	9 (6–11)	15 (11–18)	8 (6–10)	7 (5–8)
Walking ≤ 1 km; 1 km < Cycling ≤ 5 km	50 (37–62)	25 (18–31)	25 (19–31)	36 (26–45)	17 (12–21)	19 (14–24)
Walking ≤ 2 km; 2 km < Cycling ≤ 5 km	50 (38–63)	25 (19–31)	25 (19–32)	36 (27–45)	17 (13–22)	19 (14–24)

Table 4
New cases of diseases prevented (incidence) over the life course of the Melbourne adult population (95% uncertainty interval).

Scenarios/Diseases	Ischemic heart disease	Stroke	Alzheimers disease and other dementias	Diabetes type 2	Breast cancer	Chronic myeloid leukemia	Colon cancer	Head and neck cancer	Liver cancer	Lung cancer	Multiple myeloma	Stomach cancer	Uterine cancer	Depression
All trips														
Walking ≤ 1 km	5,922 (5,024 to 6,831)	3,749 (3,156 to 4,342)	8,202 (5,252 to 11,173)	3,372 (2,729 to 4,026)	162 (82–241)	24 (7–41)	204 (-17 to 423)	630 (272–1,009)	161 (53–271)	830 (662–997)	256 (115–401)	221 (108–336)	77 (29–126)	38 (28–48)
Walking ≤ 2 km	19,540 (16,803 to 22,337)	12,635 (10,833 to 14,461)	18,719 (11,829 to 25,672)	16,729 (13,573 to 19,959)	1,041 (659–1,418)	41 (9–73)	966 (106–1,824)	2,189 (949–3,530)	714 (298–1,142)	2,983 (2,109 to 3,858)	955 (419–1,511)	905 (476–1,346)	351 (167–536)	163 (122–204)
Cycling ≤ 2 km	18,165 (15,588 to 20,795)	11,935 (10,196 to 13,696)	18,679 (11,823 to 25,600)	15,486 (12,562 to 18,481)	907 (561–1,249)	41 (9–73)	867 (65–1,667)	2,110 (914–3,404)	654 (263–1,056)	2,872 (2,077 to 3,667)	918 (407–1,449)	848 (442–1,267)	323 (149–497)	155 (116–194)
Cycling ≤ 5 km	33,592 (28,988 to 38,339)	21,043 (18,150 to 24,018)	23,350 (14,288 to 32,509)	36,197 (29,345 to 43,219)	2,551 (1,739 to 3,354)	41 (4–80)	1,684 (260–3,102)	3,738 (1,607 to 6,040)	1,331 (607–2,074)	4,739 (3,180 to 6,298)	1,451 (572–2,358)	1,508 (801–2,237)	717 (365–1,072)	420 (313–531)
Walking ≤ 1 km; 1 km < Cycling ≤ 2 km	18,697 (16,049 to 21,400)	12,216 (10,447 to 14,009)	18,854 (11,942 to 25,832)	15,782 (12,805 to 18,832)	934 (578–1,286)	41 (10–74)	896 (72–1,718)	2,146 (932–3,459)	671 (271–1,082)	2,925 (2,113 to 3,737)	939 (417–1,480)	868 (453–1,296)	331 (153–509)	158 (118–198)
Walking ≤ 1 km; 1 km < Cycling ≤ 5 km	34,056 (29,389 to 38,869)	21,282 (18,362 to 24,281)	23,514 (14,401 to 32,725)	36,403 (29,514 to 43,462)	2,574 (1,754 to 3,385)	42 (4–80)	1,710 (268–3,148)	3,764 (1,620 to 6,079)	1,345 (614–2,096)	4,781 (3,209 to 6,354)	1,468 (580–2,383)	1,525 (811–2,260)	724 (368–1,081)	423 (314–533)
Walking ≤ 2 km; 2 km < Cycling ≤ 5 km	34,544 (29,827 to 39,407)	21,498 (18,566 to 24,519)	23,400 (14,307 to 32,592)	36,992 (29,988 to 44,169)	2,655 (1,817 to 3,484)	42 (4–80)	1,753 (291–3,209)	3,782 (1,625 to 6,111)	1,371 (632–2,130)	4,805 (3,195 to 6,415)	1,469 (575–2,391)	1,543 (822–2,285)	738 (378–1,099)	425 (316–537)
Commuting trips														
Walking ≤ 1 km	197 (165–230)	127 (106–149)	77 (43–110)	241 (195–287)	7 (4–10)	0 (0–1)	5 (-2 to 11)	36 (16–58)	7 (2–12)	33 (27–39)	10 (4–16)	10 (5–15)	2 (1–4)	6 (5–8)
Walking ≤ 2 km	758 (650–874)	483 (413–555)	348 (200–491)	1,053 (854–1,257)	68 (42–94)	1 (0–2)	26 (-2 to 55)	95 (41–152)	25 (10–40)	95 (69–120)	31 (14–49)	27 (14–41)	22 (10–33)	20 (15–26)
Cycling ≤ 2 km	700 (598–808)	453 (386–522)	365 (214–511)	961 (779–1,148)	58 (35–82)	1 (0–2)	23 (-3 to 50)	91 (39–145)	23 (8–37)	91 (69–113)	30 (13–47)	25 (13–38)	20 (9–31)	19 (14–24)
Cycling ≤ 5 km	1,852 (1,584 to 2,143)	1,106 (947–1,277)	238 (73–395)	3,058 (2,480 to 3,650)	210 (143–277)	0 (-1 to 1)	55 (-5 to 114)	224 (96–362)	65 (29–102)	196 (133–257)	64 (25–105)	63 (32–94)	53 (27–79)	101 (75–128)

(*continued on next page*)

Table 4 (*continued*)

Scenarios/Diseases	Ischemic heart disease	Stroke	Alzheimers disease and other dementias	Diabetes type 2	Breast cancer	Chronic myeloid leukemia	Colon cancer	Head and neck cancer	Liver cancer	Lung cancer	Multiple myeloma	Stomach cancer	Uterine cancer	Depression
Walking ≤ 1 km; 1 km < Cycling ≤ 2 km	723 (618–834)	466 (397–537)	365 (214–512)	990 (803–1,182)	59 (36–83)	1 (0–2)	24 (-4 to 51)	94 (41–150)	24 (9–38)	94 (71–117)	31 (14–48)	26 (13–40)	20 (9–31)	20 (15–25)
Walking ≤ 1 km; 1 km < Cycling ≤ 5 km	1,874 (1,602 to 2,168)	1,118 (957–1,291)	239 (73–397)	3,084 (2,501 to 3,681)	211 (143–278)	0 (-1 to 1)	56 (-5 to 115)	227 (97–366)	66 (29–103)	199 (136–261)	66 (25–106)	64 (33–96)	53 (27–80)	102 (75–129)
Walking ≤ 2 km; 2 km < Cycling ≤ 5 km	1,906 (1,631 to 2,205)	1,134 (972–1,308)	223 (61–379)	3,140 (2,547 to 3,748)	219 (150–288)	0 (-1 to 1)	58 (-4 to 118)	228 (98–368)	67 (30–105)	199 (133–264)	66 (25–107)	65 (34–97)	55 (28–81)	102 (75–129)

Table 5
Deaths from diseases prevented over the life course of the Melbourne adult population (95% uncertainty interval).

Scenarios/Diseases	Ischemic heart disease	Stroke	Alzheimers disease and other dementias	Diabetes type 2	Breast cancer	Chronic myeloid leukemia	Colon cancer	Head and neck cancer	Liver cancer	Lung cancer	Multiple myeloma	Stomach cancer	Uterine cancer	Depression
All trips														
Walking ≤ 1 km	2,946 (2,583 to 3,311)	887 (806–967)	4,428 (2,810 to 6,060)	19 (15–22)	-24 (-27 to -22)	4 (1–8)	-12 (-27 to 3)	84 (33–139)	129 (41–219)	456 (365–546)	97 (39–156)	73 (32–115)	5 (-1 to 11)	0 (0–0)
Walking ≤ 2 km	9,458 (8,448 to 10,517)	2,942 (2,723 to 3,168)	10,710 (6,677 to 14,791)	95 (77–113)	45 (18–71)	7 (1–14)	6 (-68 to 81)	309 (121–514)	563 (228–908)	1,773 (1,232 to 2,314)	390 (151–640)	315 (155–481)	47 (17–77)	0 (0–0)
Cycling ≤ 2 km	8,711 (7,780 to 9,686)	2,748 (2,541 to 2,963)	10,700 (6,688 to 14,759)	88 (72–105)	29 (7–50)	8 (1–14)	-1 (-69 to 68)	297 (117–495)	515 (200–839)	1,707 (1,216 to 2,199)	376 (149–615)	295 (143–452)	42 (14–71)	0 (0–0)
Cycling ≤ 5 km	16,491 (14,712 to 18,418)	5,131 (4,719 to 5,571)	13,973 (8,407 to 19,630)	234 (190–279)	235 (152–317)	8 (0–16)	55 (-89 to 198)	606 (240–1,006)	1,088 (488–1,706)	3,007 (1,968 to 4,047)	626 (210–1,059)	582 (293–881)	113 (50–177)	0 (0–0)
Walking ≤ 1 km; 1 km < Cycling ≤ 2 km	9,001 (8,034 to 10,012)	2,825 (2,612 to 3,045)	10,798 (6,752 to 14,892)	89 (73–106)	30 (7–52)	8 (1–14)	0 (-70 to 71)	302 (119–503)	529 (206–860)	1,736 (1,236 to 2,238)	384 (152–627)	301 (147–462)	43 (15–72)	0 (0–0)
Walking ≤ 1 km; 1 km < Cycling ≤ 5 km	16,750 (14,938 to 18,710)	5,199 (4,781 to 5,644)	14,064 (8,468 to 19,753)	235 (191–280)	235 (152–317)	8 (0–16)	56 (-89 to 201)	609 (242–1,011)	1,099 (493–1,723)	3,028 (1,983 to 4,076)	632 (212–1,068)	587 (296–889)	113 (50–178)	0 (0–0)
Walking ≤ 2 km; 2 km < Cycling ≤ 5 km	17,022 (15,185 to 19,010)	5,262 (4,841 to 5,710)	13,992 (8,406 to 19,672)	238 (194–284)	247 (162–332)	8 (0–16)	60 (-87 to 207)	612 (242–1,016)	1,120 (507–1,751)	3,042 (1,973 to 4,114)	631 (209–1,070)	594 (301–899)	116 (52–181)	0 (0–0)
Commuting trips														
Walking ≤ 1 km	86 (76–97)	27 (24–31)	51 (28–73)	2 (2–2)	2 (1–2)	0 (0–0)	0 (-1 to 1)	7 (3–12)	5 (1–9)	26 (21–30)	5 (2–8)	4 (2–6)	1 (0–1)	0 (0–0)
Walking ≤ 2 km	380 (335–428)	132 (119–146)	232 (133–329)	10 (8–12)	8 (4–12)	0 (0–1)	1 (-3 to 4)	20 (8–33)	22 (9–36)	66 (48–84)	15 (6–24)	13 (6–20)	4 (2–7)	0 (0–0)
Cycling ≤ 2 km	348 (307–393)	123 (111–136)	242 (141–341)	9 (7–11)	6 (3–9)	0 (0–1)	1 (-3 to 4)	19 (8–32)	20 (7–33)	63 (47–79)	14 (5–23)	12 (6–18)	4 (2–6)	0 (0–0)
Cycling ≤ 5 km	943 (829–1,073)	307 (272–343)	195 (74–311)	30 (24–35)	37 (25–49)	0 (0–0)	5 (-4 to 13)	52 (22–85)	58 (25–91)	149 (99–199)	33 (11–55)	32 (16–48)	13 (6–19)	0 (0–0)
Walking ≤ 1 km; 1 km < Cycling ≤ 2 km	359 (317–406)	126 (113–140)	243 (142–342)	9 (7–11)	7 (3–10)	0 (0–1)	1 (-3 to 4)	20 (8–33)	21 (8–34)	66 (49–82)	15 (6–24)	12 (6–19)	4 (2–7)	0 (0–0)
Walking ≤ 1 km; 1 km < Cycling ≤ 5 km	953 (837–1,084)	309 (275–346)	196 (75–313)	30 (24–36)	37 (25–50)	0 (0–0)	5 (-4 to 14)	53 (22–86)	58 (26–92)	152 (101–202)	34 (11–56)	33 (16–49)	13 (6–19)	0 (0–0)
Walking ≤ 2 km; 2 km < Cycling ≤ 5 km	972 (855–1,105)	315 (280–352)	186 (67–301)	30 (25–36)	39 (26–51)	0 (0–0)	5 (-4 to 14)	53 (22–87)	60 (26–93)	152 (100–204)	34 (11–56)	33 (17–50)	13 (6–20)	0 (0–0)

4. Discussion

Replacing short car trips with active transport modes (walking and cycling) can lead to important population health benefits. We estimated health gains as large as 739,000 HALYS for the Melbourne adult population for the following scenario: replacing short car trips for all purposes under 2 km with walking; and replacing short car trips between 2 km and 5 km with cycling. Greater gains in HALYs for all simulated scenarios (in comparison to life years) indicate that a shift from car travel to active modes would prevent premature mortality and increase quality of life. This includes reductions in new cases of chronic diseases and deaths, mostly from Alzheimer's disease and other dementias, ischemic heart disease, stroke and type 2 diabetes. These results also demonstrate the influence and importance of non-health sector interventions to improve population health and reduce economic burden on health systems. For example, investment in walking and cycling infrastructure would support active transport behaviours and health. Our separate analysis of all trip types and commute trips shows the importance of active transport incentives for the whole population. Interventions targeting commute trips imply that only 6% of trips by those aged 65 years and older would benefit. Targeting those in retirement age is essential for healthy aging and supporting transport related physical activity is a simple means for improving health for all ages but especially for this age group.

4.1. Strengths and limitations

Our study provides the first assessment of active travel scenarios for Melbourne using simulation modelling of health impacts and modelling a population over time. It also builds on our previous research conducted in Brisbane, Australia (Zapata-Diomedi et al., 2017). However, in comparison to our previous work, this modelling is based on an improved methodology using the latest evidence for associations between physical activity and disease outcomes (Garcia et al., 2023; Pearce et al., 2022). In this study we included 14 chronic diseases associated with physical activity compared to five in our previous study and improved modelling exposure of physical activity by developing a micro-simulation model (Abbas and Woodcock, 2020; Garcia et al., 2021) that used continuous relative risks. Traditionally, relative risks for the association of physical activity and health outcomes are available in categories (i.e. inactive, insufficiently active, active, highly active) (Danaei et al., 2009), with most of the evidence on transport and health to date using categorical relative risks. The impact of using categorical relative risks results in under- or overestimations from the calculation of categorical PIFs (Barendregt and Veerman, 2010) and associated power loss (Greenland, 1995). Our study benefited from progress in this field led by the ITHIM work started in the UK (Woodcock et al., 2009) and a recent R-package to obtain relative risks for a range of chronic diseases over a continuous distribution of physical activity (Garcia et al., 2022). This allowed us to map each modelled individual directly to the disease relative risks from the baseline and scenario being modelled. Additionally, we made major improvements in accessibility to our models for other researchers by developing an R-based workflow to run the model and we provide the full set of inputs required to generate outcomes and the complete set of outcomes.

Despite best effort, some limitations remain. Firstly, while the physical activity component of our micro-simulation model considers population heterogeneities, such as age, sex and socio-economic status, our health model does not. This implies that we assumed that the only differentiating factor for rates of diseases and all-cause mortality is attributable to age and sex. This approach might be underestimating health outcomes given that in Australia prevalence of chronic conditions are highest amongst socioeconomically disadvantaged populations (Health and Welfare, 2019). We made our greatest effort for transparency of methods, however, we used the publicly available and free tool Dismod II to calculate disease case fatality given that it is not publicly available. We reported in the supplementary material the derivation of Dismod II data, however, it is a manual process. In future research we will overcome this issue by using the R package Disbayes (Jackson et al., 2023) which is fully transparent and reproduceable. In addition, we assumed that increased active transport translates into increased physical activity, ignoring any potential replacement effect with recreational physical activity. Our modelling assumes that current transportation patterns will remain unchanged in the future. However, global initiatives aimed at decarbonising the transport sector may lead to increased levels of transport-related physical activity. Unfortunately, due to the lack of data on transportation trends, we were unable to incorporate such trends into our study and consequently our results may be overestimated.

4.2. Comparison with past research

Findings from simulation studies from high income countries showed that the greatest health impact from shifting car travel to active modes is from improvements in physical activity relative to other risk factors (air pollution, noise, injuries) (Mueller et al., 2015). Previous Australasian evidence indicates that the greatest health benefits come from increased physical activity (Mizdrak et al., 2019; Zapata-Diomedi et al., 2017). For example, a simulation study for New Zealand used the proportional multi-state life table method and estimated undiscounted gains of 17 HALYs per 1,000 people for a scenario where car trips under 1 km were replaced with walking. (Mizdrak et al., 2019) We estimated 30 HALYs per 1,000 people for replacing all types of trips under 1 km by car with walking. Our study, however, included 14 diseases associated with physical inactivity in comparison to only five in the New Zealand study. In comparison to past studies, we did not discount health outcomes. Discounting is a standard practice in conducting economic evaluations of health care interventions (Drummond et al., 2005), and health modelling studies of active interventions have used standard discount rates (e.g., 3%, 5%, 7%) applied to health technology assessment (Mueller et al., 2015). Discounting future health benefits implies a value judgment that future health is worth less than current health and particularly impactful for prevention interventions, like active transport, with long term health benefits (Bonneux and Birnie, 2001; West, 1996). Hence, in this research we did not discount health outcomes. In this study, we also simulated the impact of active travel on individuals' overall levels of physical

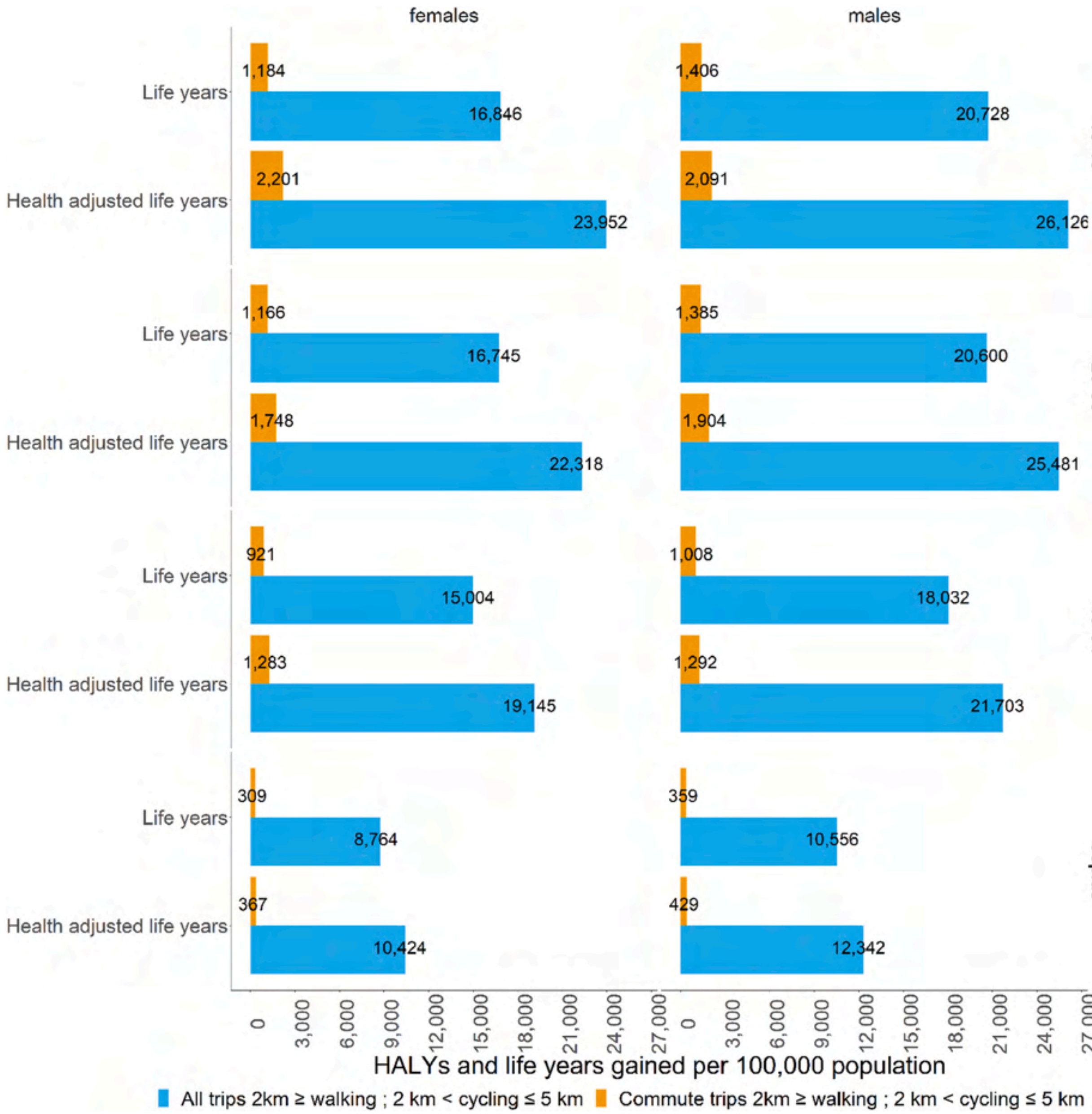

Fig. 5. HALYs and life years gained per 100,000 population for selected scenarios by sex and age groups.

activity. Our findings are corroborated by empirical evidence. A cross-sectional study conducted in England demonstrated that individuals who engaged in cycling for transport purposes were between three to four times more likely to meet the national physical activity guidelines." (Stewart et al., 2016).

4.3. Ambitious scenarios and local policies and infrastructure

Our modelling shows that significant health gains could be achieved if Melbourne residents would walk and cycle instead of driving their car for trips under 5 km. Australia has one of the lowest levels of cycling amongst high income countries (1.4% mode share) (Buehler and Pucher, 2021) and our analysis indicates that Melbourne aligns with this national average with a 1.3% mode share for cycling. While our scenarios might not be easy to achieve in Melbourne, they are within the range of cycling and walking mode share observed in other parts of the world. For example, cycling mode share observed in the Netherlands is 27% (Buehler and Pucher, 2021; Goel et al., 2021). This is comparable to our more ambitious scenarios for replacing all car trips under 5 km with cycling (30% mode share, Fig. 4) and all car trips of less than 1 km with walking and between 2 km and 5 km with cycling (26% mode share, Fig. 4). For

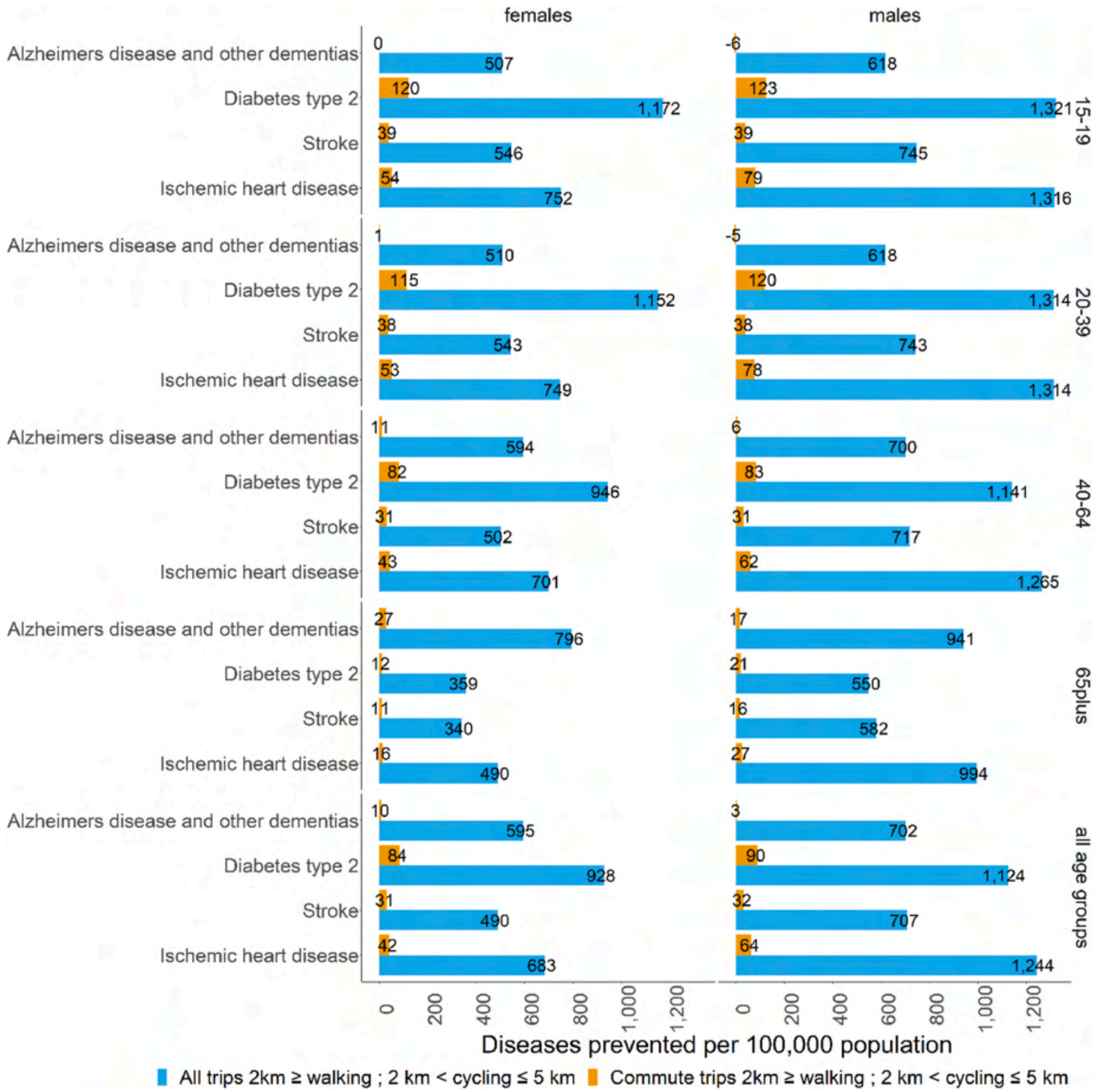

Fig. 6. New cases of diseases prevented per 100,000 population for selected scenarios and diseases by sex and age group.

walking, the current mode share (for all trip stages) is considerably higher than cycling at 27%. The greatest increase in mode share achieved is in the scenario that replaces car trips under 2 km with walking (38% mode share, Fig. 4). Worldwide comparable data for walking mode share is more limited, but a comparison of countries included in the C40 Alliance shows that Zaragoza in Spain has the highest level of walking for a high-income country with 46% of mode share, followed by Barcelona with 33% (C40 Cities Climate Leadership Group, N/D).

In Melbourne, multiple planning strategies and infrastructure policies indicate government support for increasing the mode share of active forms of travel. For example, the regional planning strategy *Plan Melbourne* contains the policies 'Create pedestrian-friendly neighbourhoods' and 'Create a network of cycling links for local trips' (State Goverment of Victoria, 2017). Further policies relate to developing strategic cycling corridors for commuting purposes, locating destinations, such as schools, near public transport and building safe cycling and walking routes to them. In addition, the 20-min neighbourhood concept is a crucial part of Plan Melbourne and forms the basis for more detailed planning and transport strategies. For example, the latest Precinct Structure Planning Guidelines for new communities (Victoria State Goverment, 2021) are based on the concept of the 20-min neighbourhood and they aim to provide better active transport infrastructure. Similarly, like other major cities in the world, local and state government in Melbourne deployed

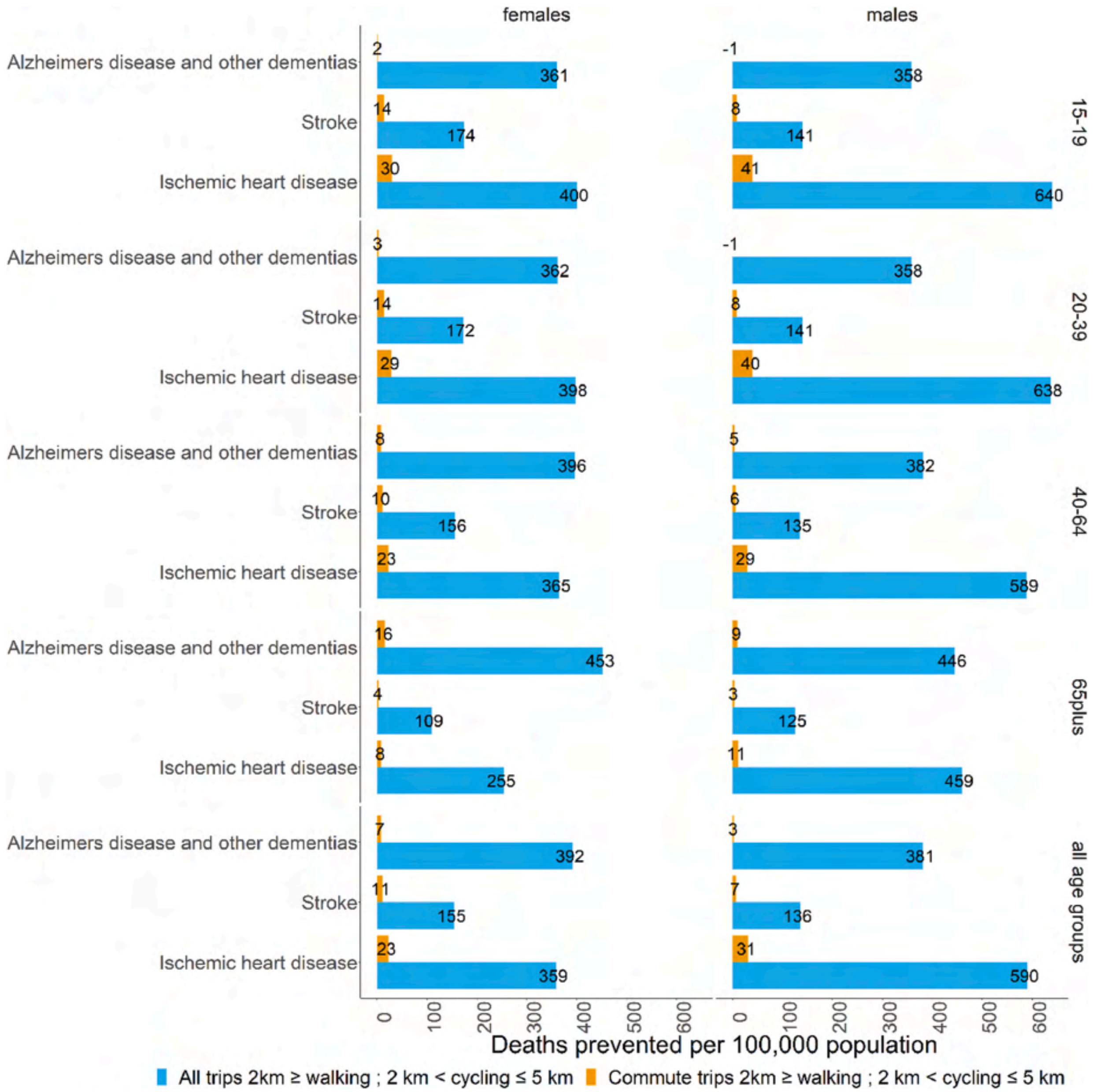

Fig. 7. Deaths from diseases prevented per 100,000 population for selected scenarios and diseases by sex and age groups.

temporary cycling infrastructure segregated from traffic as trials during the COVID-19 pandemic as fewer cars were on the road because of increased working from home and other measures to reduce the spread of the disease (VicRoads, 2021). However, conversion to permanent infrastructure is contingent on observing increased use, public discussion, and obtaining further funding to support more permanent and safe infrastructure.

5. Conclusions

This study contributes to the literature by demonstrating the health benefits from transitioning from car travel to active modes. This is the first study, to our knowledge, to use a combined micro and macro simulation approach to model health impacts of transportation in Australia. Our results support policies for compact cities, such as 20-min neighbourhoods. In addition, we contribute by making our code open source for reproducibility purposes.

Our results indicate important health benefits when transitioning from private car travel to active modes. However, important differences were identified when comparing age groups. While younger populations benefit from living longer due to doing more transport-related physical activity, they develop more diseases later in life because of their longer life expectancy. In addition, we demonstrated that health benefits from commute trips decrease as populations age. Active transport interventions should target the whole population to ensure healthy and active living for older age cohorts and be included in multi-sectoral strategies that support healthy aging.

The most important limitations of this study are the lack of heterogeneity inclusions, such as socioeconomic status and ignoring the potential replacement effect of transport physical activity for recreational physical activity.

Efforts for future research should be placed in transitioning to a full micro-simulation approach to be able to quantify subgroup benefits such as benefits for the most socioeconomically disadvantaged. Equity evidence for active transport might be helpful for policy makers to direct funding where the greatest health benefits would be accrued. In addition, simulation studies should aim for fully open sourced code for reproducibility purposes, transparency and sharing of knowledge.

Authors' statement

BZ-D conceived the research, designed the study, developed the methods, and drafted the manuscript. AA originally developed the R code for the PMSLT with BZ-D and AB developed the R code for the expanded version of the code including scenarios and the micro-simulation with BZ-D and improved the original code by AA and BZ-D for the PMSLT. LG contributed to drafting the manuscript and reviewed multiple versions of it. AK and MD reviewed the manuscript and edited. JW supported the R code development and provided scientific guidance for the micro-simulation model. AA provided technical guidance with the ITHIM-R suite of models.

Financial disclosure

None to declare

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 and core available, see section 2.6 Data availability and code

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The model in this paper partially builds upon the ITHIM-Global model (https://github.com/ITHIM/ITHIM-R/tree/master**)**.

This research was undertaken in partnership with the Australian Urban Observatory (auo.org.au) that houses a freely accessible previous version of this modelling work using the Transport Health Assessment Tool for Melbourne (THAT-Melbourne).

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jth.2023.101628.

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