Technical Report

# Transport Health Assessment Tool for Melbourne

# (THAT-Melbourne)

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The Transport Health Assessment Tool for Melbourne can be accessed in the Australian Urban Observatory at **auo.org.au/transport-health-assessment**

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# Introduction

The model that forms the basis of the Transport Health Assessment Tool for Melbourne (THAT-Melbourne) quantifies physical activity-related health impacts arising from a range of scenarios where short car trips are replaced by walking, cycling or a combination of both, based on data from metropolitan Melbourne.

It is well known that physical activity improves health and reduces the burden of diseases associated with inactivity and sedentary behaviour. In Australia in 2015, physical inactivity contributed to 20% of the disease burden (mortality and morbidity) from diabetes, some types of cancer (bowel, uterine, breast), dementia and cardiovascular diseases.[1]

Overall, physical inactivity was responsible for 2.5% of the total disease burden with 55% of the adult population (18 years of age and older) not meeting the National Physical Activity Guidelines.

In Melbourne (Figure 1), a small proportion of trips were made by active modes (walking and cycling) compared to the use of private cars (Figure 2, Analysis of VISTA survey data [2]). Replacing short car trips of up to 10kms by walking and cycling would contribute greatly to increasing population levels of physical activity and reduce the burden of diseases.

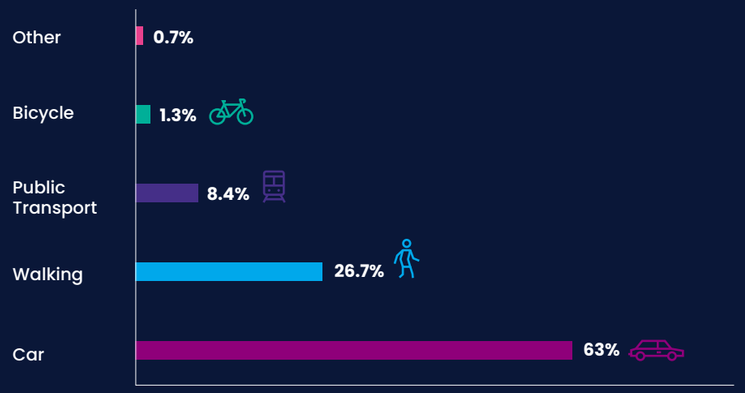
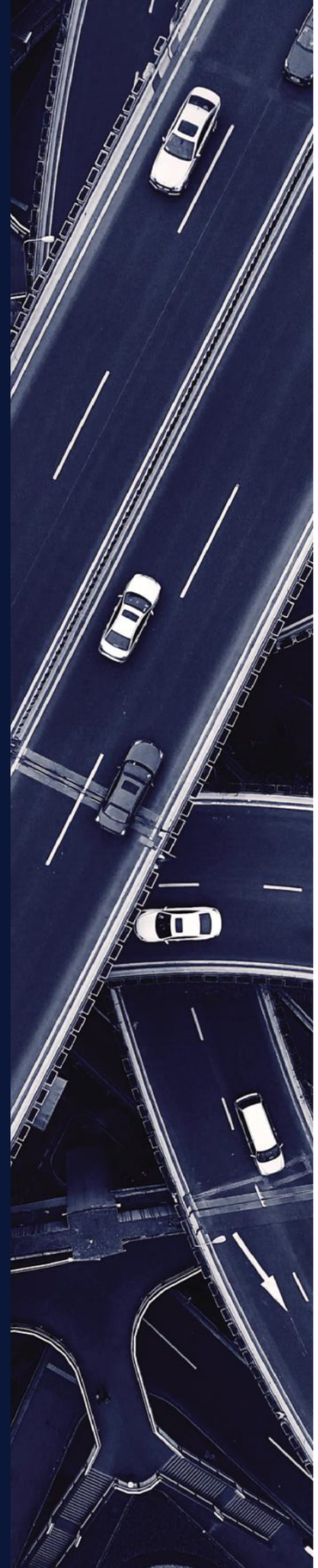



**Figure 1: Transport mode share for Melbourne**

Source: Analysis of the Victorian Integrated Survey of Travel and Activity (VISTA) 2017-18. Analysis conducted on trip stages.



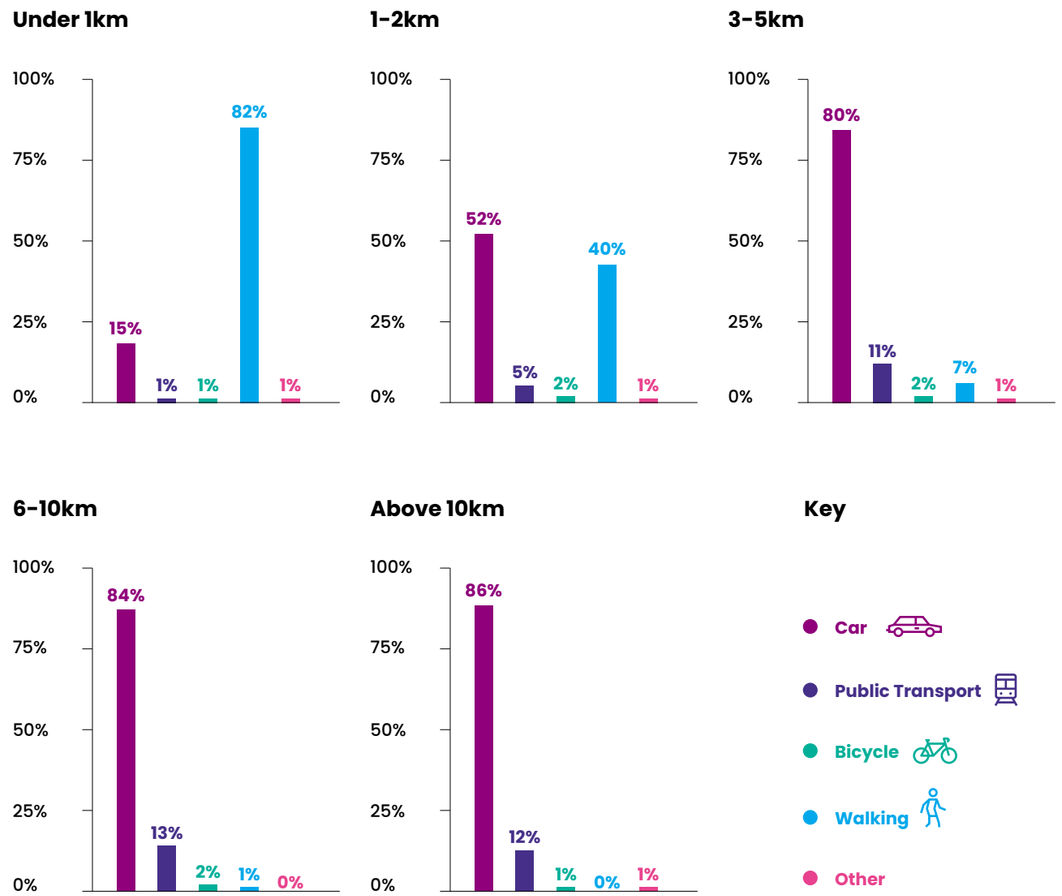



**Figure 2: Transport mode share by distance category for Melbourne**

Source: Analysis of the Victorian Integrated Survey of Travel and Activity (VISTA) 2017-18. Analysis conducted on trip stages.

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# Scenarios

The Transport Health Assessment Tool for Melbourne allows users to choose from a variety of scenarios for replacing short car trips with walking, cycling or a combination of both, accommodating options for trip purpose; age groups; and sex (Table 1).

The maximum possible distance to be replaced is 2 kms for walking and 10 kms for cycling. Note that distances replaced correspond to stages of a trip, for example, a trip to work may include multiple stages including walking to a train station, the train ride itself, and walking from the station to the place of employment.

**Trip purposes were grouped into:**

1: all trips, which includes work-related, education, leisure, shopping, pick-up or drop-off someone/ something, personal business, other, accompany someone, and at or going home;

2: commuting, which includes work-related and education trips.

**Table 1: User inputs for the scenarios**

| User Input | Options |
|---|---|
| **Trip purpose** | |
| **All** | Work-related, education, leisure, shopping, pick-up or drop-off someone/ something, personal business, other, accompany someone, at or go home |
| **Commuting** | Work-related and education |
| **Replace car trips with** | |
| **Walking** | 0 - 1km<br>0 - 2km |
| **Cycling** | 0 - 2km<br>0 - 5km<br>0 - 10km |
| **Both walking and cycling:** | Walking trips 0 - 1km, cycling trips between 1 - 2km<br>Walking trips 0 - 1km, cycling trips between 1 - 5km<br>Walking trips 0 - 1km, cycling trips between 1 - 10km<br>Walking trips 0 - 2km, cycling trips between 2 - 5km<br>Walking trips 0 - 2km, cycling trips between 2 - 10km |
| **Sex** | All<br>Male<br>Female |
| **Age** | 16 - 19 years<br>20 - 39 years<br>40 - 64 years<br>65 plus years<br>All age groups |

03

# Methods

## 03.1 Overview

The modelling framework is depicted in Figure 3.

**The model consists of three main sections:**

1. Scenarios;

2. Potential Impact Fractions (PIF); and

3. Proportional multi-state life table (PMSLT).

We developed a hybrid model [3], where the scenarios and PIF calculations are at the individual level (micro-simulation) and the PMSLT calculations are at the macro level (aggregated by age and sex groups) (macro-simulation).

The micro-simulation calculates the impact of changes in physical activity due to the scenarios on disease risk at the individual level. Seven diseases related to physical activity were included: ischemic heart disease, stroke, diabetes mellitus type 2, colon cancer, lung cancer, and for females only: breast and uterine cancers. Disease risk measures the probability of becoming diseased given exposure to a risk factor, such as physical inactivity. The potential impact fraction (PIF) measures the proportional change in disease risk when exposure to a risk factor changes.

PIFs for the included diseases were estimated at the individual level and the average PIFs by age and sex were used to estimate the effect of changes in physical activity on incidence rates for the included diseases.

We refer to this as the disease process in the macro-level simulation. Incidence is the number of new cases of disease over a time period and changes in incidence impact on the number of people living with a disease in later years (prevalence), quality of life and mortality.

Overall changes in quality of life and mortality from all included diseases are measured within the macro-simulation via the life table, which is discussed in the sections that follow.

The macro-simulation model used was the proportional multi-state life table (PMSLT). The model simulates 5-year age groups and sex cohorts for 1) the base case or business-as-usual scenario; and 2) for the chosen scenario, with baseline year 2017. PMSLTs for each age and sex cohort are simulated for the base case and scenario, and the difference amongst them is initiated by changes in incidence in the scenario disease processes. The population cohorts within the PMSLT are simulated until everyone dies or reaches the age of 100.

Estimated outcomes are prevented new cases of chronic diseases and mortality, 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.

The PMSLT for physical activity was originally developed for the *Assessing the Cost-Effectiveness in Prevention* project (ACE-prevention).[4] The version used here also borrows from developments for the Integrated Transport Health Impact Model (ITHIM) [5, 27] originally developed for the United Kingdom with later adaptations used in other locations including United States, Canada and Brazil (https://www.mrc-epid.cam.ac.uk/research/research-areas/public-health-modelling/ithim/).

The model was initially developed in Excel and for the version presented here we used the statistical computing software R. Dr Zapata-Diomedi completed some components of the code development while on placement at the MRC Epidemiology Unit, University of Cambridge under the supervision of Dr James Woodcock.

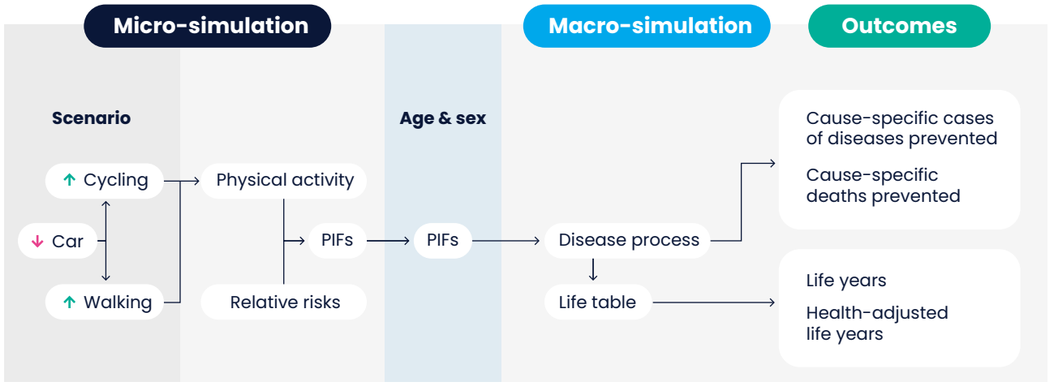


**Figure 3: Analytical framework for the Transport Health Assessment Tool for Melbourne**

## 03.2 Micro-simulation

Potential Impact Fractions (PIFs) (Equation 1) are calculated using relative risks (RR) for the seven aforementioned diseases related to the physical activity risk factor for the base case and chosen scenarios.

The methods developed in the ITHIM-R project were used here.[5]

Inputs for the PIFs' calculations are energy expenditures based on individual marginal metabolic equivalent of task per hour (mMET-hours) per week and disease relative risks. METs are metabolic equivalent of tasks and measure the energy expenditure required to carry out physical activity, expressed as a multiple of the resting metabolic rate.[6]

Marginal METs only consider energy expended above the resting metobolic rate.

$$PIF_{disease} = \frac{RR_{base\ case} - RR_{scenario}}{RR_{base\ case}}$$

**Equation 1: PIFs calculations**

Each individual in the modelled population has a base case and scenario mMET-hours, where the scenario is modified by the additional walking or/and cycling attributable to the scenario. The derivation of mMET-hours and the relative risks calculations are explained in the sections that follow.

## mMET-hours

A matched population of individuals was created by matching the Victorian Integrated Survey of Travel and Activity (VISTA) 2017-2018 [2] persons file and the National Health Survey (NHS), 2017-18, Basic CURF [7] to derive individual base case and scenario mMET-hours per week.

The matching process is depicted in Figure 4. Sampled individuals from NHS were randomly allocated to the VISTA persons file based on age, sex, socio-economic status (SES), whether they walk for transport, whether they walked at least 2 hours per week for transport and whether they worked. The matching process had a success rate of nearly 99%, which implies that only 1% of the VISTA persons had no matching physical activity (PA) variables from the NHS.

We created a trip file for each of the scenarios, which contained base case and scenario mode of travel for each trip stage along with base case time and distance and scenario time. A trip may have up to nine stages. Scenario time was derived from the original stage distance from car trips divided by speed for the replacing mode, either walking or cycling, based on the median speed for each mode across the VISTA sample of 4 (25th & 75th percentiles, 2.6, 5.12) km per hour for walking and 11 km per hour (25th & 75th percentiles, 7.4, 15) for cycling.

We created time variables for each person for the base case and scenario by adding up the time for all stages by mode in a trip and appending them to the matched population.

In this manner, everyone in the matched population had measures for total time by mode for the base case and scenario. The data is for one day, and we derived weekly total travel time and distance by mode by multiplying by 7.

mMET-hours per individual in the matched population for the base case and scenario were derived from the sum of the product of hours spent weekly doing transport walking, transport cycling, vigorous physical activity for leisure, moderate physical activity for leisure and walking for leisure by their corresponding mMET-hours scores (Table 2).

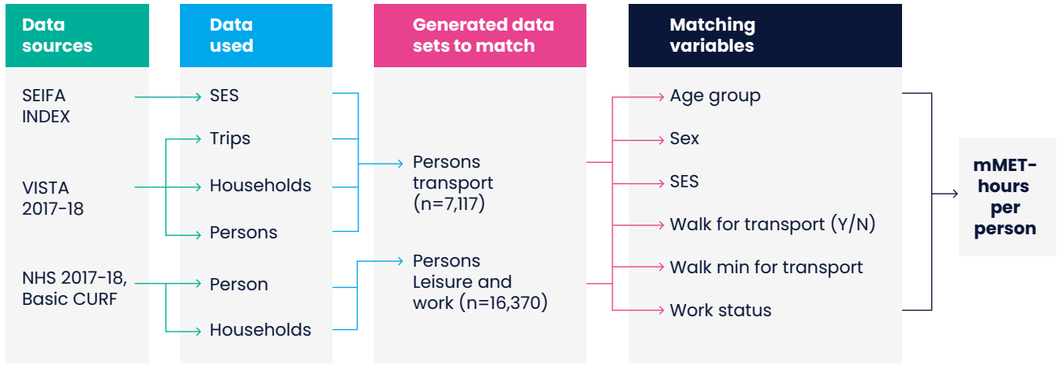


**Figure 4: Analytical framework for deriving mMET-hours**

**Table 2: MET scores**

| Physical activity | mMETs | Description |
|---|---|---|
| **Walking for transport** | 2.5 | Code 17190 (walking, 2.8 to 3.2 mph, level, moderate, surface, firm) [1] |
| **Cycling for transport** | 5.8 | Code 1011 (bicycling to and from work, self-selected pace; METs=6.8; mMET=6.8-1) [1] |
| **Walking for leisure** | 2.5 | Code 17160 (walking for pleasure) [1] |
| **Moderate physical activity** | 3.5 | See reference [8] |
| **Vigorous physical activity** | 7 | See reference [8] |

[1] Note: Codes relate to METs from the Compendium of physical activities, see reference [9].

Transport walking time in the matched population was derived from multiplying one day per week from the VISTA survey by 7, whilst transport walking from the NHS was available for the whole week.

Hence, we compared results for the mean overall and per time categories to check the accuracy of the walking for transport data in this model (Table 3).

In the matched population the mean hours spent in transport walking per week for the base case was 1.12 whilst data from the NHS was relatively close at 1.04.

**Table 3: Comparison of walking for transport between NHS and VISTA datasets.**

| | NHS | | VISTA - Person file | |
|---|---|---|---|---|
| Time category | Mean | Frequency | Mean | Frequency |
| **0 hours** | 0.00 | 73% | 0.00 | 74% |
| **0 - 1 hours** | 0.70 | 3% | 0.57 | 1% |
| **1.1 - 2 hours** | 1.91 | 8% | 1.40 | 3% |
| **2.1 - 5 hours** | 3.39 | 11% | 3.30 | 13% |
| **5.1 - 10 hours** | 7.48 | 3% | 6.78 | 7% |
| **> 10 hours** | 22.20 | 1% | 13.11 | 1% |

The two data sources used to derive the individual mMET-hours are discussed on the following page.



### Victorian Integrated Travel and Activity Survey (VISTA)

The latest VISTA survey conducted across the period 2017-18 for Greater Melbourne and Geelong was used. Randomly selected households were asked to complete the household form with each adult individual required to complete a travel diary for a single specified day (with an adult completing the travel diary for children). The survey aims to capture average travel behaviour.

The Greater Melbourne survey included 3,543 households, 7,117 individuals and 23,166 trips. Travel data was collected for all individuals aged above 5 in each household.

We limited the analysis to individuals aged 16 and above given that the scenarios consist of replacing car trips and the legal driving age in Melbourne commences at age 16 under the full supervision of a licensed driver.

The travel diary asked respondents about travel and activities on a particular travel day, specifically: 1) all travel over the whole day, from 4:00 am on the travel day until 4:00 am the next day, 2) all trips to be included, even short trips (like walking to lunch or going for a jog). VISTA also includes people who do not travel on the travel survey day.

### National Health Survey (NHS)

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.

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. Table 4 outlines types of physical activity data collected in the NHS.

### Relative risks physical activity

Relative risks (RRs) compare the likelihood of an adverse event occurring with the likelihood of the same event not occurring depending on the level of exposure to a risk factor or protective factor.

In this model the protective factor is physical activity. We used the RRs for physical activity-related diseases from the meta-analysis developed by the University of Cambridge Public Health Modelling Group [28] for breast cancer, colon cancer, ischemic heart disease, stroke and lung cancer as well as the RRs reported in reference [8] for diabetes, which were derived from mortality and incidence combined.

All diseases have a threshold beyond which there are no benefits from increases in mMETs-hours, except for diabetes [5].

These thresholds are 35 mMET-hours for colon, breast and uterine cancers, and ischemic heart disease; 10 mMET-hours for lung cancer and 32 mMET-hours for stroke.

The meta-analysis provided data for the RRs for each of the diseases and mMET-hours per week. Hence, each individual in the matched population described above has a corresponding RR for the base case and scenario which are then used to calculate the individual level PIFs. Average PIFs for each of the diseases by age and sex modify incidence in the disease life tables in the PMSLT.

**Table 4: National Health Survey variables**

| Type of activity | Definition | |
|---|---|---|
| **Walking for fitness, recreation and sport** | Must have carried out for at least 10 minutes continuously. | |
| **Walking to get from place to place** | Excludes activities such as walking around a shopping centre as people tend to frequently pause while shopping. | Must have carried out for at least 10 minutes continuously. |
| **Moderate intensity exercise** | Comprises activities that caused a moderate increase in the heart rate or breathing of the respondent (e.g. gentle swimming, social tennis, golf). | Excludes any previously identified walking as well as household chores, gardening or yard work, and any activity carried out as part of a job. |
| **Vigorous intensity exercise** | Comprises activities that caused a large increase in the respondent's heart rate or breathing (e.g. jogging, cycling, aerobics, competitive tennis). | Excludes any previously identified walking as well as household chores, gardening or yard work, and any activity carried out as part of a job. |
| **Strength or toning exercises** | Activities designed to increase muscle strength or tone, such as lifting weights, resistance training, pull-ups, push-ups, or sit ups. | Includes any strengthening and toning exercises or activities already mentioned. |
| **Workplace physical activity** | Usual physical activity while at work on a typical work day.<br><br>Must have carried out for at least 10 minutes continuously.<br><br>Moderate activity in the workplace was defined as activity that caused a moderate increase in the heart rate or breathing of the respondent (e.g. brisk walking or carrying light weights). | Vigorous activity in the workplace was defined as activity that caused a large increase in heart rate or breathing (e.g. carrying or lifting heavy loads, digging or construction work). |

## 03.3 Macro-simulation

The PMSLT has been used to simulate health impacts of changes in exposure to health risk factors for population groups (e.g. age and sex cohorts).

Figure 5 is a schematic representation of the PMSLT. The two PMSLT components are a life table and disease process for each of the modelled diseases.[10]

These two components are modelled for both the base case and scenario for each sex and 5-year age cohorts. The life table models the survival for the cohort and includes for a given age interval the probability of dying, the number of people alive, life years and the rate of total prevalent years lived with disability (pYLD total). Total pYLD is the proportion of life that is lost due to diseases and injury (disability) and adjusts life years to derive the measure of Health-adjusted life years (HALYs).

For each of the seven diseases and their disease processes, incidence, prevalence and disease specific mortality are calculated. Transition probabilities between states are used in the derivation of incidence to adjust the transition from healthy to diseased and case fatality from disease to dead from the diseases [11] (see Table 5 for data inputs).

The PIFs by age and sex cohort explained in sections 3.1 and 3.2 modify incidence in the scenario's disease process. Because type 2 diabetes is a risk factor for ischemic heart disease and stroke [12, 13], the impact of changes in type 2 diabetes due to the scenario are calculated (see section 3.3.1). Disability weights (section 3.3.2 Table 5), which reflect the health loss attributable to disease on a scale from 0 (perfect health) to 1 (equivalent to death) [14] are multiplied by disease prevalence to derive disease specific pYLDs.

The difference between pYLDs and mortality rates between base case and scenarios disease processes are collected in the scenario life table to modify all-cause mortality and pYLD total. Cohorts in the general life table are modelled from the baseline year (2017) until they die or reach the age of 100.

The health outputs are measured as the difference between the base case and scenario disease processes and life table. 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.[10]

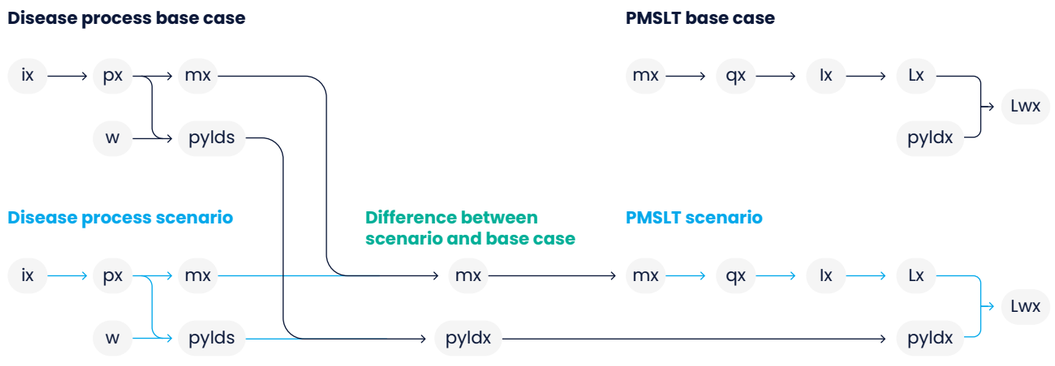


**Figure 5: PMSLT analytical framework**



Figure 5 describes the interaction between life table parameters and disease parameters. All the parameters are age specific denoted with x, i is incidence, p is prevalence and m is mortality, w is a disability adjustment, pyld is prevalent years lived with a disability, q is probability of dying, l is number of survivors, L is life years, Lw is disability adjusted life years. A change in physical activity translates into changes in incidence (ix), which changes disease specific prevalence (px) and mortality (mx). For presentation purposes we only depict one disease process, however, in this study we modelled 7 diseases (ischemic heart disease, stroke, breast cancer, colon cancer, type 2 diabetes, uterine cancer, and lung cancer).

### PIF type 2 diabetes

Type 2 diabetes is a risk factor for ischemic heart disease and stroke [12, 13], hence, we also included the PIFs for stroke and ischemic heart disease as a function of changes in diabetes as shown in Equation 2 and summarized in Table 5 for males and females respectively within the PMSLT.

$$PIF = \frac{-(Prevalence_{scenario} - Prevalence_{base\ case}) * (RR-1)}{Prevalence_{base\ case} * (RR-1) + 1}$$

$Prevalence_{scenario}$ represents the prevalence of type 2 diabetes after the scenario, whilst $Prevalence_{base\ case}$ represents the prevalence for type 2 diabetes in the base case and RR represent the relative risk for stroke or ischemic heart disease respectively.

**Equation 2: PIF for diabetes**

For ischemic heart disease and stroke, we calculated the combined PIF according to Equation 3 given that these two diseases have two risk factors in the model: physical inactivity and type 2 diabetes:

$$PIF_{combined} = \prod_{r} 1 - (1 - PIF_{risk})$$

**Equation 3: Combined PIF**

**Table 5: Relative risks for the association between diabetes and stroke and ischemic heart disease by sex [12, 13]**

| | Relative Risk (95% confidence interval) | |
|---|---|---|
| Disease | Female | Male |
| **Ischemic heart disease** | 2.82 (2.35, 3.38) | 2.16 (1.82, 2.56) |
| **Stroke** | 2.28 (1.93, 2.69) | 1.83 (1.60, 2.08) |

## Disability weights

Disability weights (DW) are derived from disease specific prevalent years lived with disability (YLD) and disease specific prevalence by age group (5 years) and sex. Data for YLDs prevalence is from the Global Burden of Disease (GBD) data for 2017.

An age and sex specific-correction was introduced to counteract the effects of accumulating comorbid illnesses in the older age groups as shown in Equation 4. Interpolation was used to derive rates per single year of age from 5-year age intervals.

$$DW_{adjusted} = \frac{\frac{YLD_{disease}}{P_{disease}}}{1-YLD_{total}}$$

**Equation 4: DW adjusted**

Equation 4 Where $YLD_{disease}$ is the YLD mean number per age and sex for a given disease, $P_{disease}$ is the prevalence as reported in the Global Burden of Disease study for a given disease by age and sex and $YLD_{total}$ is the total YLD rate per age and sex.

## Data inputs

Data for the proportional multi-state life table model (PMSLT) include inputs for the life table. Specifically, this includes inputs for population, mortality rates and prevalent years lived with disability and rates for all causes (i.e., Years Lived with Disease or YLD); and, for the diseases process incidence and case fatality. Here we prepared inputs for the Melbourne population.

When local inputs were available, these were used, otherwise, we used state or nationally representative inputs. Table 5 describes all data inputs for the PMSLT. Each of the PMSLT components and related data processing are explained below in Table 6.

**Table 6: PMSLT data inputs**

| Component | Data needs | Input data | Data processing |
|---|---|---|---|
| **Life table** | Population numbers and mortality rates | Population Greater Melbourne [15] by 5-year age groups and sex and death rates by single year of age and sex [16]. | Population data is from the ABS 2016 Census. Mortality rates are for Victoria given that future projections for mortality were available for Victoria and not for Melbourne. Deaths rates projections were available by 1-year age intervals and sex from 2017 (baseline to 2066) based on the medium population growth assumption. |
| **Life table** | All-cause YLDs | Global Burden of Disease (GBD) study by 5-year age groups and sex [17]. | GBD data is in five-year age groups, interpolation to derive one-year age group. |
| **Disease process** | Disability weights, incidence and case fatality | Disability weights were derived from disease specific YLDs [17]. Incidence and case fatality were derived using DISMOD II software [18]. | Table 6 outlines DISMOD II data processing and data inputs. Disability weights were calculated by dividing disease specific YLDs by prevalence and adjusted by all cause YLDs. |
| **Disease process** | Future trends to apply to incidence and case fatality | Trends in cancers for incidence [19] and mortality [20]. Trends for cardiovascular diseases and diabetes were not available. These were derived from past data [21-23]. | Derived from past data when unavailable. |



## Incidence and case fatality

We used Australian Institute of Health and Welfare (AIHW) incidence and mortality cancer data for 2017 for Australia and GBD data for Australia for other diseases for the year 2017 to derive incidence and case fatality inputs for colon cancer, lung cancer, ischemic heart disease, stroke and type 2 diabetes, and for females only breast and uterine cancer.

We used Dismod II (free at https://www.epigear.com/index_files/dismod_ii.html) to derive internally consistent inputs for incidence and case fatality and to generate missing data. For example, the GBD study provides data for incidence, prevalence and disease mortality, however, not case fatality.

For cancers we used AIHW given that the GBD data was derived assuming remission for cancers (except for long life sequelae) [23], but in our model we assumed no remission for diseases. In addition, AIHW generates data for colon cancer and lung cancer, while the GBD only provides estimates for larger disease groups (colon and rectum cancer and tracheal, bronchus, and lung cancer). Dismod II is a separate tool, therefore, here, we provide information relating to any processing of the original data (Table 7).

**Table 7: Disease processing DISMOD II**

| Disease | Collection data | Disease inputs | ICD-10 codes[1] | Process |
|---|---|---|---|---|
| **Diabetes mellitus type 2** | Population and mortality rates [17]. | Incidence, prevalence and mortality [17]. | E08-E08.11, E08.3-E08.9, E12-E12.1, E12.3-E13.11, E13.3-E14.1, E14.3-E14.9, R73-R73.9 (all diabetes) | Remission set to zero. |
| **Ischemic heart disease** | Population and mortality rates [17]. | Incidence, prevalence and mortality [17]. | I20-I21.6, I21.9-I25.9, Z82.4-Z82.49 | Remission set to zero and higher weight to prevalence input (half bar). |
| **Stroke** | Population and mortality rates [17]. | Incidence, prevalence and mortality [17]. | G45-G46.8, I60-I62, I62.9-I64, I64.1, I65-I69.998 | Remission set to zero and higher weight to prevalence input (half bar). |
| **Breast cancer (females)** | Population (2017) and deaths data (2017) for Australia (Australian Bureau of Statistics) [24, 25]. | Incidence and mortality [26]. | C50 | Remission set to zero. |
| **Uterine cancer (females)** | Population and deaths data for Australia (Australian Bureau of Statistics) [24, 25]. | Incidence and mortality [26]. | C54-C55 | Remission set to zero. |
| **Colon cancer** | Population and deaths data for Australia (Australian Bureau of Statistics) [24, 25]. | Incidence and mortality [26]. | C18 | Remission set to zero. |
| **Lung cancer** | Population and deaths data for Australia (Australian Bureau of Statistics) [24, 25]. | Incidence and mortality [26]. | C33-C34 | Remission set to zero. |

[1]Note: ICD-10 codes refer to those from the International Statistical Classification of Diseases and Related Health Problems.

### Diseases' trends

Table 8 outlines methods used to derive diseases' trends.

**Table 8: Diseases' trends**

| Input | Inputs | Assumptions | Data processing |
|---|---|---|---|
| **Incidence cancers** | Australian Institute of Health and Welfare [20] forecast from 2017 to 2020. | Applied to incidence and case fatality. | We derive an annual trend as the log difference between the age standardized rate in 2020 and 2017 divided by the difference in years. |
| **Case fatality cancers** | Australian Institute of Health and Welfare [20] forecast from 2014 to 2020 for mortality. | Applied to incidence and case fatality. | See above. |
| **Cardiovascular diseases incidence** | Australian Institute of Health and Welfare [22] hospitalization past trends (actual data) from years 2001 to 2018. | Applied to incidence and case fatality. Trends were applied to ischemic heart disease and stroke. | Future Age standardized rates (ASR) were first derived from ASR from past trends by sex using linear regression for predominantly increasing trends and log-linear regression for decreasing trends. Trends were estimated up to year 2023. Annual trends were derived as above (ln(ASR2023/ASR2018)/years). |
| **Cardiovascular diseases case fatality** | Australian Institute of Health and Welfare [22] mortality past trends (actual data) from years 2001 to 2018. | See above. | Future Age standardized rates (ASR) were first derived from ASR from past trends by sex using linear regression for predominantly increasing trends and log-linear regression for decreasing trends. Trends were estimated up to year 2023. Annual trends were derived as above (ln(ASR2023/ASR2018)/years). |
| **Diabetes incidence** | Australian Institute of Health and Welfare [23] mortality past trends from years 1997 to 2023 for diabetes as the underlying or associated cause of death. | Trends only applied to incidence. | Same as above with forecast up to year 2023. |

## 03.4 Assumptions

The PMSLT models the future health trajectories of age and sex cohorts. Trends were applied to diseases' incidence and all-cause mortality to reflect future changes.

However, trends were not applied to physical activity from the National Health Survey and the VISTA survey. 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 (baseline) will have the physical activity and travel patterns observed in those aged 25-29 years of age today when they reach that age (by sex).

## 03.5 Uncertainty intervals

Ninety-five percent uncertainty intervals [6] were determined for all outcome measures by Monte Carlo simulation (1000 iterations) (Table 9).

Intervals were derived 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 input data.

**Table 9: Distributions for Monte Carlo simulation**

| Inputs | Uncertainty/Parameters | Source |
|---|---|---|
| **Relative risks physical activity** | Sample from normal distribution, defined by the mean and standard deviation derived from the difference between the upper and lower bound divided by 1.96, truncated to 0. | https://shiny.mrc-epid.cam.ac.uk/meta-analyses-physical-activity/ |
| **Relative risks diabetes** | Log-normal, see table 4. | See table 4. |

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