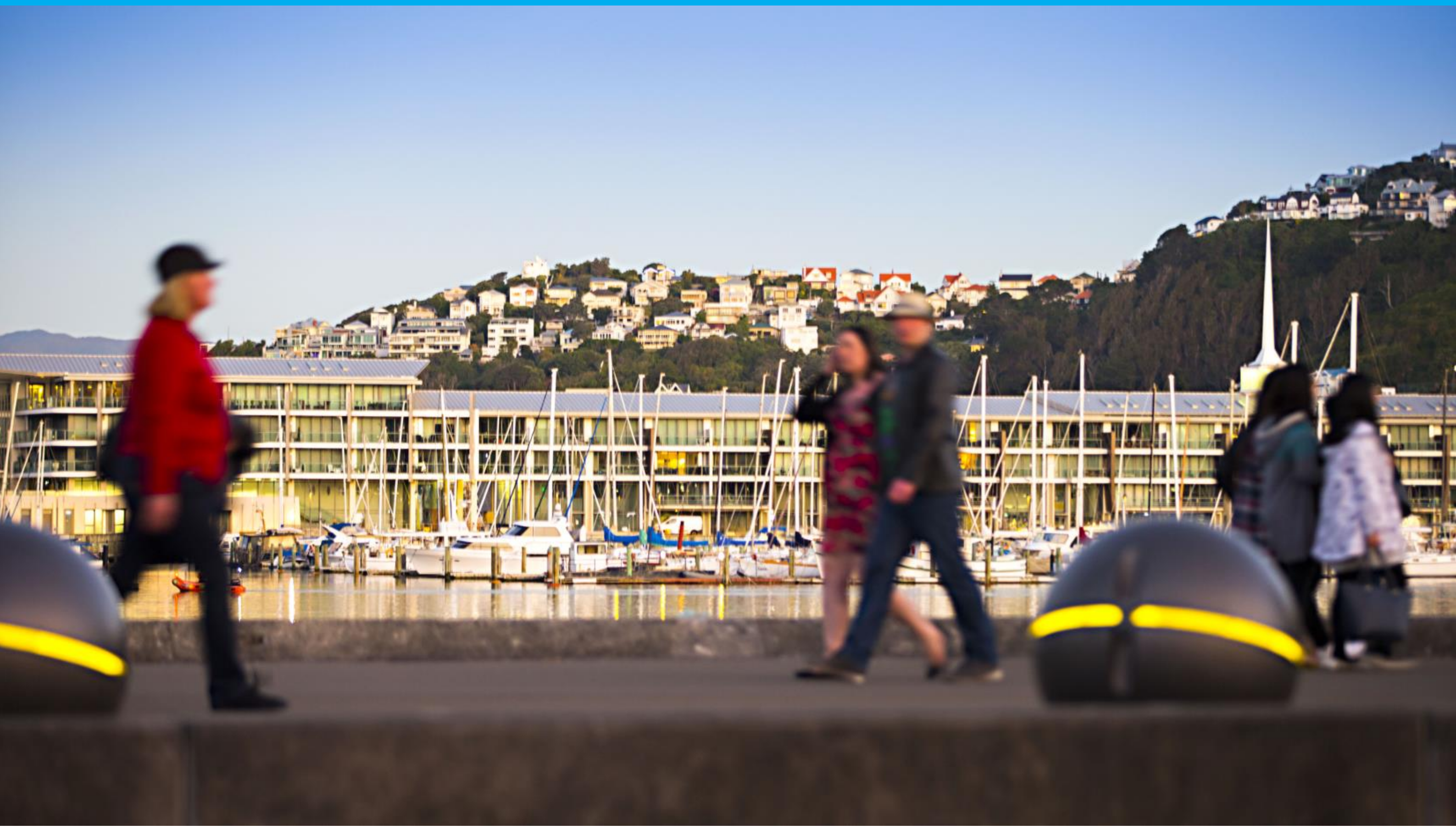
Absolutely Positively **Wellington** City Council

Me Heke Ki Pōneke

Statement of Evidence of Órla Hammond on behalf of Wellington City Council

19 January 2023



Version	Date	Author(s)	Reviewer
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Glossary

Abbreviation/Term	Definition
ArcGIS	A geographic information system for working with maps and geographic information maintained by the Environmental Systems Research Institute (Esri).
BMI	Body Mass Index
CCPA	California Consumer Privacy Act
CDPP	City Design and Place Planning
Council	Wellington City Council
DEM	Digital Elevation Model
GDPR	General Data Protection Regulation
GIS	Geographic Information Science/System
GNSS	Global Navigation Satellite Systems
GPS	Global Positioning System
Km/h	Kilometres per hour
LCD	Least-cost-distance
m/s	Metres per second
MS	Microsoft
NPS-UD	National Policy Statement on Urban Development 2020
NPS-UDC	National Policy Statement on Urban Development Capacity 2016
Pedestrian travel rate	The speed at which a person walks
RMA	Resource Management Plan
SAR	Search and Rescue
THF	Tobler's Hiking Function, also known as Tobler's rule
Topography	The landforms and features of land surfaces, specifically mountains, valleys, lakes, rivers, craters, etc.
USMA	United States Military Academy
Walkable catchment	"The area an average person could walk from a specific point to get to multiple destinations" (Ministry for the Environment 2020)
Walkability	A planning term for defining the accessibility of mixed-use amenities in high-density neighbourhoods that can be reached on foot (Dovey and Pafke 2022)
WCC	Wellington City Council

1. Executive Summary

1. Travel rate models, such as walkable catchments, using pedestrian walking speeds are commonly used to understand the dynamics of individuals' movement through space. This analysis has many applications such as city planning, emergency evacuation routes, and access to community services. Wellington City Council reviewed and updated its walking network using pedestrian infrastructure pathways (such as, footpaths, crossings, and tracks), topography, and walking rate calculations.

2. A walking network is a collection of paths and tracks a pedestrian uses when travelling to different locations. Information, such as travel rate and slope, is added to these paths and tracks to model 'real-world' conditions. This allows estimated walkable catchment areas to be calculated.

3. Creating a walking network for Wellington City was a cross-council project and included input from the District Plan, City Transport and Infrastructure, Community Services, and Parks, Sport, and Recreation teams, as well as many others. It contains the following information:
    - Path, tracks, and popular routes through parks
    - Pedestrian tunnels and bridges
    - Controlled crossing points with an average wait time
    - Uncontrolled crossing points with an average wait time
    - Slope gradient
    - Low, moderate, and high walking speed estimates based on direction of travel, for example walking uphill versus downhill

4. By including this information in our walking network, we can model 'real-world' conditions in our walkable catchments.

5. Walking speed is highly subjective. There is no such thing as an 'average walking speed' that can be applied to everyone. It is generally assumed that the walking speed for the average person is 5km/h (1.4m/s). When we began reviewing scientific literature, we found that this average speed was too fast for low and moderate speed walkers. We studied articles that measured pedestrian travel rate ranges for different age groups and abilities to get a more accurate picture. These articles included studies from all around the world and included diverse groups such as young children and older adults.

6. We then accessed anonymous travel mode data for Wellington collected by the fitness tracker application, Strava, to see how the international literature compared to the travel rate data

collected by Wellingtonians. As Strava is a fitness application, the data is potentially biased towards people who are fitness conscious and may not represent the general population.

7. With this potential limitation in mind, we did some testing and data collection using our own test subjects with known variables. Staff from Wellington City Council tracked their movements for two weeks, covering approximately 48km of Wellington's walkable areas. Using a combination of all this information, we came up with an average for low (0.93m/s), moderate (1.1m/s) and fast (1.35m/s) walking speeds on flat slope. The Lorentz mathematical function was used to extrapolate speeds across different slope gradients. Using the Lorentz function, any value of slope angle θ (in degrees) can be input to calculate the estimated travel rate for that slope based on the WCC Walking Network Model.

2. Purpose of Report

8. My name is Órla Hammond. I am the Team Lead for the City Insights GIS Team at Wellington City Council.

9. I have a Master of Science in Geographic Information Science (GIS) from Technological University Dublin (formerly Dublin Institute of Technology) where I wrote my dissertation on the use of least-cost-pathway analysis to aid search and rescue teams in mountainous areas.

10. I have seven years' experience in geographic information systems and science. I have been with Wellington City Council (WCC) since 2019 as a GIS Analyst supporting the District Planning team. I have provided data, analysis, mapwork, and web application development for the Spatial Plan and Draft District Plan.

11. My evidence is given on behalf of WCC in relation to the development of the WCC Walking Network Model. This model provided outputs that support activities related to the District Plan.

12. This report:
    - Discusses the need for a walking network model when calculating a walkable catchment,
    - Describes the literature review undertaken to identify a suitable travel rate function for calculating 'walking speed',
    - Describes the methodology used to update WCC's existing walking network model and test the outputs, and
    - Describes how the walking network model was used to support the development of the Spatial Plan and the District Plan.

2.1 Code of Conduct

13. Although this is a Council Hearing, I have read the Code of Conduct for Expert Witnesses contained in the Practice Note issued by the Environment Court effective 1 January 2023. I have complied with the Code of Conduct when preparing my written statement of evidence and I agree to comply with it when I give any oral evidence.

14. Other than when I state that I am relying on the evidence or advice of another person, this evidence is within my area of expertise. I have not omitted to consider material facts known to me that might alter or detract from the opinions I express.

15. Any data, information, facts, and assumptions I have considered in forming my opinions are set out in the part of the evidence in which I express my opinions. Where I have set out opinions in my evidence, I have given reasons for those opinions.

3. Introduction

16. The walkability of cities and neighbourhoods has seen a surge of interest in the past decades. The initial interest was motivated by the environmental goal of encouraging pedestrian over car-based urbanism. This interest has since expanded to include walkability as a key factor in improving the health, communities, and economy of cities (Talen & Koschinsky 2013). Walkability connects many divergent fields, including transportation planning, health, urban planning and design, sustainability, and sociology (Daniel & Burns 2018).

17. The promotion of walking is essential to central and local governments due to increased pressure on the transit system and environmental concerns (Finnis & Walton 2008). A key principle of contemporary urban planning and design theory allows citizens in urban areas to access facilities and services within an easy walking distance (Meeder et al. 2017). People are unlikely to walk more than 10-minutes to public transit networks and they are inclined to choose private transport for journeys more than 30-minutes in urban areas (Finnis & Walton 2008). It is essential for central and local governments to understand what a walkable distance is when planning their urban environments.

18. A key consideration for understanding walkability is pedestrian walking speed, or travel rate. Conceptual walkable catchments do not represent the reality of the impact the street network has on pedestrian travel rates (Aghabayk et al. 2021, Finnis & Walton 2008). A walking network is a collection of paths and tracks a pedestrian uses when travelling to different locations. Information, such as travel rate and slope, is added to the network to model 'real-world' conditions. This allows estimated walkable catchment areas to be calculated.

19. The characteristics of a walking network, such as topographic features, attraction points, and street network topology, are influential in measuring the walkability of urban areas (Gates et al. 1982). Travel rate tends to be under-considered when reviewing pedestrian characteristics and when it is considered, it is often a single speed representing the most common user (Pinna &

Murrau 2018). Waka Kotahi (New Zealand Transport Agency) characterises factors that have the greatest influence on walking speed by:

- pedestrian characteristics (e.g., age, gender, and physical/cognitive conditions),
- route characteristics (e.g., path width, gradient, surfacing, shelter, and attractiveness),
- trip characteristics (e.g., walking purpose, route familiarity, trip length and encumbrances), and
- environmental characteristics (e.g., weather conditions) (Waka Kotahi 2009).

20. Based on these characteristics (above), a range of mathematical travel rate models have been developed to quantify walking speeds (Campbell et al. 2019). In literature, the estimated travel rate of pedestrians is a notable parameter in pedestrian safety studies (Aghabayk et al. 2021), evacuation times in case of emergencies (Wood & Schmidtlein 2012), transit stations (Finnis & Walton 2008), walkways, and pedestrian crossings (Webb et al. 2017). Thus, travel rate is a fundamental parameter in modelling pedestrian movement during normal day-to-day and emergency activities.

21. Wellington City Council (WCC) has created a walking network for Wellington City using pathways and tracks, topography, and pedestrian travel rates resulting from this review. Prior to this walking network review and update, WCC hosted a Walking Network Model that was developed in 2010. This model estimated pedestrian travel rates to measure the level of accessibility to town centres and public transport infrastructure via walking. Since 2010, there has been additional research into the range of factors which can impact the pedestrian travel rate. Given the diverse topography and characteristics of Wellington City, it is important to evaluate the range of existing mathematical models available to determine which function is best suited to calculate pedestrian travel rate in our walking network dataset.

22. The WCC Walking Network Model will provide the evidence base for policy decisions, such as the District Plan Review and Let's Get Wellington Moving, and give effect to Government policy and direction. It is imperative the walking network dataset is up-to-date and feeds into a model that is based on up-to-date research and accurate travel rate calculations.

23. The current travel rate model will be refined and updated to take into consideration the recent research on pedestrian travel rate. This revised model will be tested against data captured in the field by the fitness application, Strava, to see how international literature compares to the travel rate data collected by Wellingtonians.

4. Background and Literature Review

24. Previous studies have investigated numerous variables influencing walking travel rates (Campbell et al. 2017, Daniel & Burns 2018, Finnis & Walton 2008, Talen & Koschinsky 2013). Walking route properties such as slope, the presence of stairs, and 'attractiveness' (Campbell et al. 2019, Edwards & Dulai 2018, Pingel 2010), and pedestrian characteristics such as age, gender, and physical condition (Aghabayk et al. 2021, Finnis & Walton 2008) are the two primary focus areas for travel rate studies. Interestingly, most studies tend to model walkability using a flat street network without considering the ground topography and pedestrian characteristics (Daniel & Burns 2018). This report has reviewed the walkability literature that takes walking route properties and pedestrian characteristics into consideration to develop an understanding of their impact on travel rate.

25. Travel rate models using pedestrian walking speeds and geospatial analysis have been used to understand the dynamics of individuals' movement through space and time (Middleton 2009). Since the original proposal of walking speed by Scottish Mountaineer William Naismith in 1892, (known as 'Naismith' Rule'), there have been many attempts to calculate approximate walking catchments in various scenarios. These scenarios include search and rescue operations (Ciolli et al. 2006), identifying tsunami evacuation (Wood & Schmidtlein 2012) and traffic light crossing times (Webb et al. 2017).

26. Most studies used "Naismith's Rule" as a starting point for their calculations which states a travel rate of 4.8km/h (1.3m/s) on flat terrain. This rule assumes reasonable fitness, 'typical' terrain, and 'normal' conditions (Naismith 1892). Since Naismith's original proposal, there have been modifications proposed by Tranter (1965) and Langmuir (1984), among others. These modifications seek to build upon Naismith's original concept by incorporating features such as fitness, terrain type, and downhill slope (Irmischer & Clarke 2018).

27. A review of more recent literature illustrates several different approaches to estimate walking speeds. The most widely used existing models are a function of slope, where:
    - Walking rate decreases when traveling uphill due to increased effort required by the walker (Naismith 1892, Tobler (cited in Campbell et al. 2019))
    - Walking rate decreases on downhill slopes as they get steeper, and the walker needs to break against gravity (Langmuir 1984, Campbell et al. 2019, Pingel 2010)
    - Walking rate decreases with increasing slope both uphill and downhill, but not symmetrically on either side of a 0° slope (Pingel 2010, Tobler (cited in Campbell et al. 2019).

28. Although the relationship between uphill and downhill travel seems intuitive, the extent to which walking speed rates are impacted by changes in slope differ between travel rate models. Most models show that steeper slopes cause slower walking speeds, regardless of the walker travelling uphill or downhill (Campbell et al. 2019).

4.1. Wellington City Council's 2010 Walking Network Model

29. Before this review, a Walking Network Model was developed for Wellington City in 2010. This work was initiated by the District Plan team who required analysis of residential areas to determine the level of walkability to key centres and the proximity of these areas to public transport infrastructure (Wellington City Council 2010). Building this model highlighted factors that complicated determining walkability in Wellington City, such as topography, footpath access, and infrastructure barriers. As with this review, the previous Walking Network Model aimed to incorporate these barriers into the network.

30. Prior to developing the 2010 Walking Network Model, proximity analysis was performed using buffer distances, rather than time. Buffer distances take a starting point, area, or line, and extend in all directions to a fixed distance (Esri 2022a). This method does not include impedances to travel (such as slope or lack of accessway) therefore it tends to overestimate the achievable distance compared to what is practically possible using the street network. (Figure 1).

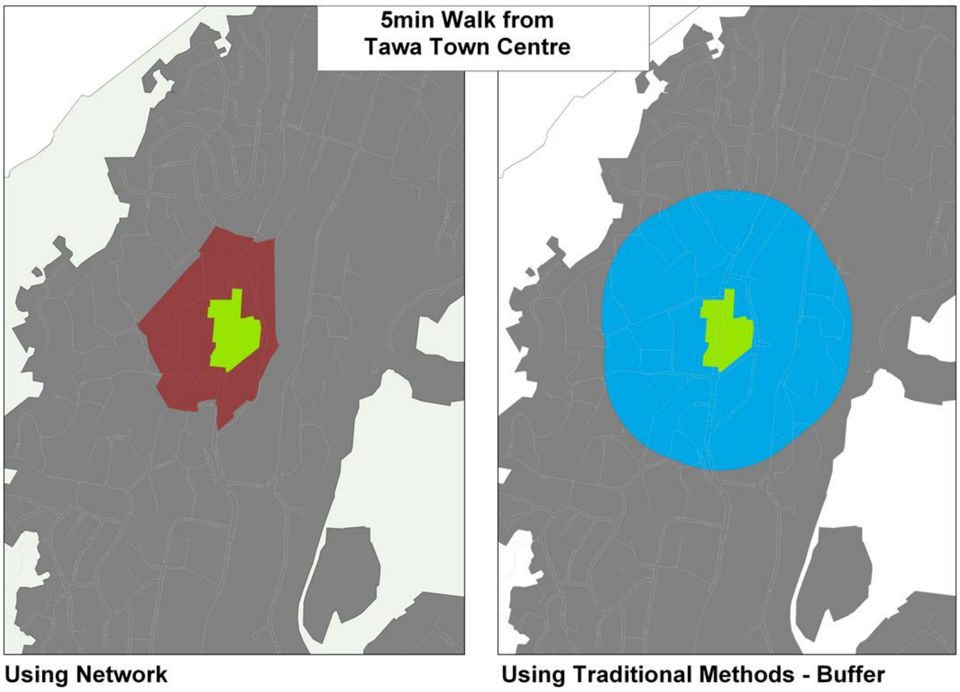

Figure 1: Map comparing the network method to the buffer method (Wellington City Council 2010).

31. A walking network dataset was created using the footpath centrelines and crossings data maintained by the Transport and Infrastructure Team, park walking tracks maintained by Parks,

Sport, and Recreation Team, and additional data captured during the development phase to improve connectivity (Wellington City Council 2010). This was a static dataset that required manual and resource intensive updates.

32. The walking network dataset incorporated pedestrian travel rates that were based on a table of walking efficiency from Ciolli et al. (2006). This was graphed in MS Excel, used to fit regression lines, and create formulas for slope versus travel rate. The formulas were used in ArcGIS field calculator (Esri 2018) to calculate a static travel rate for each line segment in both directions, uphill and downhill (Wellington City Council 2010).

33. Due to a lack of data ownership, clear business rules, and insufficient resourcing, this dataset was not sufficiently maintained. This meant there were gaps (e.g., where new developments have taken place) and the travel rate calculations had not been reviewed to reflect the current literature.

4.2. Commonly Used Travel Rate Functions

4.2.1 Summary

34. For this report, the review of existing work was split into three groups: most common functions, slope as a function of travel rate, and pedestrian characteristics as a function of travel rate. Several functions that were used in, or formed the basis of, pedestrian travel rate studies were identified. The most common functions were:
    - Naismith's Rule (1892)
    - The Tranter correction to Naismith's Rule (1965)
    - The Langmuir correction to Naismith's Rule (1984)
    - Tobler's Hiking Function/Tobler's Rule (1993)

35. Other, more recent studies chose to deviate from these functions and identified, what they deemed, more appropriate functions. Campbell et al. (2019) reflected on previous studies examining the relationship between slope and travel rate (Figure 2). They highlight how past studies contain very small sample sizes and tend to result in one mathematical function. They collected test data and compared three different distribution curves to identify which function best fitted human behaviour. They determined when modelling moderate and fast travel rates, the Laplace function was most appropriate and when modelling slower travel rates, the Lorentz function was most suitable. This is discussed in more detail in section 4.3.

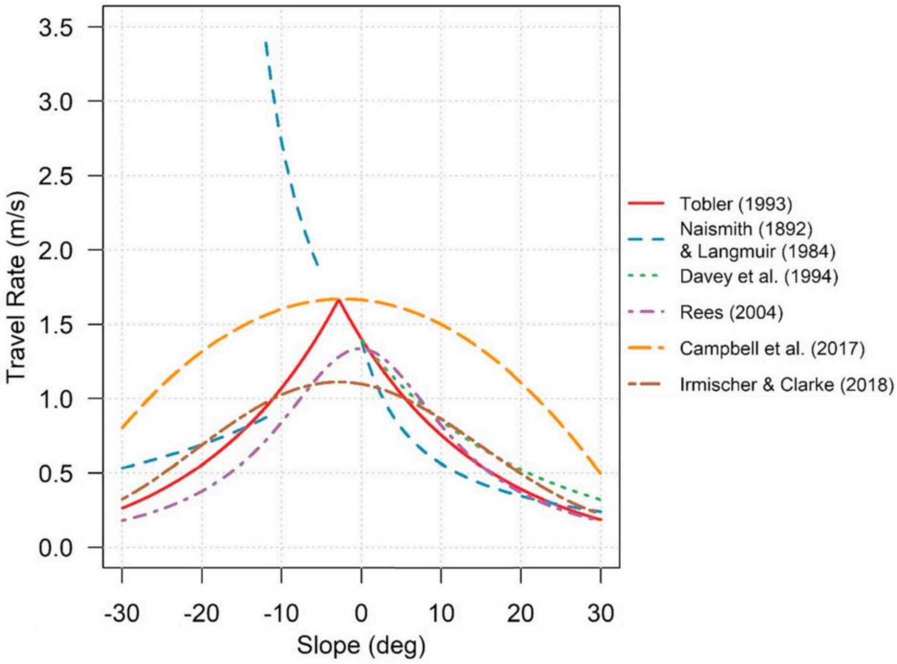

Figure 2: "Existing slope-travel rate functions, here downhill slopes are negative and uphill slopes are positive." (Campbell et al. 2019).

36. Irmischer and Clarke (2018) collected data from test subjects and compared it with Naismith's Rule and Tobler's Hiking Function. They determined that neither function was suitable for modelling travel rates in hilly terrain.

4.2.2. Naismith's Rule

37. Naismith's Rule (equation 1) is one of the oldest and more widely used slope-travel rate functions to estimate walking speeds over cross-country terrain (Naismith 1892). This rule has been used across a variety of research and practices, for example, analysing trail usage and travel time information for recreation planning purposes, studying the perceptions of safety while moving through an urban environment, and archaeological applications, including social network analysis and archaeological site accessibility assessment (Campbell et al. 2019).

38. Naismith's Rule states "one hour per three miles on the map and an additional hour per 2000 feet of ascent" (Naismith 1892) or approximately 4.8km/h plus an additional 30mins for every 300m of vertical ascent. This rule assumes "reasonable fitness", "typical" terrain, and "normal" conditions (Naismith 1892).

$$v = \frac{1}{0.72 + 6\ \times \tan|\theta|}$$

(1) Naismith's Rule

Where v is velocity (in m/s) and θ is the slope in degrees.

39. There are some caveats to Naismith's Rule, the most notable being the small sample size and lack of values for travelling downhill. Despite this, the 4.8km/h travel rate devised by Naismith is used as the default for pedestrian travel rates for organisations such as Esri (Esri 2022d), Google (Keith.A 2021), and Waka Kotahi (Waka Kotahi 2009).

40. Since Naismith's original proposal, there have been modifications proposed by Tranter (as cited in Magyari-Sáska & Dombay 2012) and Langmuir (1984), among others. These modifications seek to build on Naismith's original concept by incorporating features such as fitness, terrain type, and downhill slope (Irmischer & Clarke 2018).

4.2.3. The Tranter Correction to Naismith's Rule

41. Tranter ((date unknown) cited in Irmischer & Clarke 2018) worked to include an individual fitness correction to Naismith's Rule. Scottish mountaineer Phillip Tranter created a correction to add pedestrian fitness, fatigue, load carried and conditions underfoot (Scarf 2007). Tranter's correction table (Figure 3) shows the measured time to walk based on fitness class considering the upslope having a baseline of 800m and an ascent of 300 m. The correction time based on this table can be higher or lower than the original Naismith time (Magyari-Sáska & Dombay 2012).

Individual fitness in minutes	Time taken in hours estimated using Naismith's rule															
	2	3	4	5	6	7	8	9	10	12	14	16	18	20	22	24
15 (very fit)	1	1.5	2	2.75	3.5	4.5	5.5	6.75	7.75	10	12.5	14.5	17	19.5	22	24
20	1.25	2.25	3.25	4.5	5.5	6.5	7.75	8.75	10	12.5	15	17.5	20	23		
25	1.5	3	4.25	5.5	7	8.5	10	11.5	13.25	15	17.5					
30	2	3.5	5	6.75	8.5	10.5	12.5	14.5								
40	2.75	4.25	5.75	7.5	9.5	11.5						Too much to be attempted				
50 (unfit)	3.25	4.75	6.5	8.5												

Figure 3: Tranter's correction table for Naismith's Rule (Wikipedia 2019)

42. In 1977, Aitken (1977, cited in Irmischer & Clarke 2018) created a correction model to Tranter's to include terrain conditions. This model noted that a person could walk at 5km/h (1.39m/s) on roads, paths, and tracks, but the walking speed will be reduced to 4km/h for all other types of terrain.

4.2.4. The Langmuir Correction to Naismith's Rule

43. Naismith's Rule does not estimate a travel rate for downhill slopes (Scarf 2007). To correct for this, Langmuir (1984) suggested a modification to Naismith's Rule. The Langmuir Correction

retained Naismith's base speed of 4.8km/h on a flat surface and proposed subtracting 10min for every 300m of descent on gentler slopes (-5° to -12°) (equation 2) and adding 10min for every 300m of descent on steeper slopes (> -12°) (equation 3) (Magyari-Sáska & Dombay 2012). The correction also assumes that slopes between -5° and 0° remain at a constant speed, which isn't seen in other studies (Campbell et al. 2019). The Langmuir correction is calculated as:

$$v = \frac{1}{0.72 - 2 \times \tan|\theta|}$$

(2) Langmuir correction on a gentle slope

$$v = \frac{1}{0.72 + 2 \times \tan|\theta|}$$

(3) Langmuir correction on a steep slope

Where v is velocity (in m/s) and θ is the slope in degrees.

4.2.5. Tobler's Hiking Function

44. Tobler's Hiking Function (also known as Tobler's Rule) is one of the most popular models for estimating travel rate as a function of slope (Campbell et al. 2019). It is calculated as:

$$v = 6e^{-3.5|tan\theta+0.5|}$$

(4) Tobler's Hiking Function

Where v is velocity (in m/s) and θ is slope (in degrees).

45. The function was created using observed data of aggregated slope-based travel isolines provided by Imhof (1950) (Campbell et al. 2019). There was no reporting of data accuracy or statistical model fit. The details (e.g., sample size) of the aggregated secondary data is also unknown which can raise questions about data quality (Campbell et al. 2019). The travel rate on flat terrain matches that of Naismith's Rule, and maximum travel rate is calculated on a 5° downhill slope (Langmuir 1984).

4.2.6. Additional Travel Rate Models

46. Davey et al. (1994) performed an experiment with two test subjects on a treadmill. This allowed the slope-travel rate function (equation 5) to be adjusted based on an individual's baseline velocity that could be sustained over an unspecified distance on a flat slope (v_0). While this function does not include values for downhill travel, it is easy to adjust, making it a more flexible

option for travel rate estimates (Campbell et al. 2019).

$$v = v_0 \times exp^{-0.049 \times \theta}$$

(5) Davey et al. 1994

Where v is velocity (in m/s), v_0 is velocity on a flat slope, and θ is slope (in degrees).

47. Rees (2004) compiled the results from 10 individual walks tracked by GPS in mountainous areas. They developed a polynomial travel rate model (equation 6) shaped like a bell curve. The model only included slope as a factor of the calculations and no other variables.

$$v = \frac{1}{0.75 + 0.09 \times tan\theta + 14.6 \times (tan\theta)^2}$$

(6) Rees 2004

Where v is velocity (in m/s) and θ is the slope in degrees.

48. The recent improvement of GPS enabled platforms (such as mobile applications and wearable devices) has enabled researchers to access crowdsourced data of user's walking and hiking trips. This availability of data can allow researchers to create more robust and accurate travel rate calculations (Campbell et al. 2019).

49. Irmischer and Clarke (2018) tracked 200 United States Military Academy recruits in real-time using GPS. They used this data to devise a slope-travel rate function (equation 7). When compared to other popular functions (Tobler's Rule and Naismith's Rule with the Langmuir Correction), they found their data was better aligned to a Gauss (normal distribution) curve.

$$v = 0.11 + exp^{\frac{-(100 \times tan\theta + 5)^2}{1800}}$$

(7) Irmischer and Clarke 2018

Where v is velocity (in m/s) and θ is the slope in degrees.

4.3. Travel Rate and Slope

50. Travel route properties such as topography, slopes, and the presence of stairs are among the most noticeable factors in pedestrian travel rate studies (Aghabayk et al. 2021). How changes in slope and elevation affect a pedestrian's energy and gait is well described in the field of biomechanics (Meeder et al. 2017). However, while there have been attempts at linking slope

and pedestrian travel rate in urban areas, these factors have not been researched extensively in the field of transport planning.

51. Aghabayk et al. (2021) examined the effect of walkway slope and pedestrian physical characteristics (age, gender, body mass index (BMI)) on travel rate. They tested study participants on three different slopes: flat (0%), gentle downhill and uphill (±6%), and steep downhill and uphill (±12%). When compared to flat slopes, it was found that the influence of gentle slope (±6%) on pedestrian normal travel rate is negligible, while on steeper slopes (±12%) there was a significant change in travel rate. This effect was enhanced by a pedestrian's physical characteristics. The walking speeds of elderly participants was significantly less than young and middle-aged participants (Aghabayk et al. 2021). The effects of age on pedestrian walking speed will be discussed further in the next section.

52. Irmischer and Clarke (2018) investigated navigation in a rural, woodland setting with variable terrain. They tracked 200 study subjects as they navigated undeveloped terrain using Global Navigation Satellite Systems (GNSS). They modelled the navigation speed of the study participants using Tobler's Hiking Function and Naismith's Rule with the Langmuir Correction to analyse the trajectory. Plotting the subject's speed showed there was a clear relationship between navigation speed and terrain slope that wasn't accurately represented by existing functions. The relationship between slope and speed was then modelled using an exponential function. Equations to fit the data were derived to get the best overall match for on/off road males and on/off road females (Figure 4). Irmischer and Clarke (2018) found minor differences in travel rate based on slope when they compared the Gauss curve with their collected data with Naismith's Rule and Tobler's Hiking Function. The main difference was an initial increase in speed when travelling slightly downhill, which is not observed in the Naismith and Tobler functions.

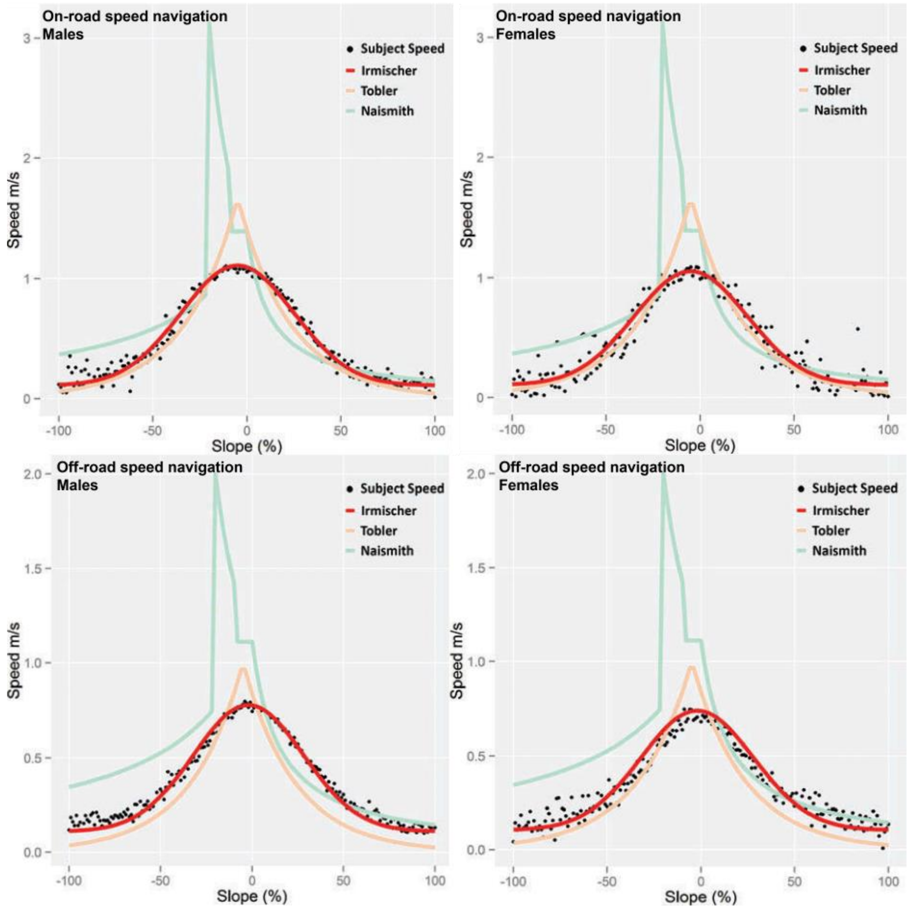

Figure 4: Irmischer model of on- and off-road navigation speeds for male (left) and female (right) study participants (Irmischer & Clarke 2018).

53. Campbell et al. (2017) investigated the effects of landscape conditions, such as slope and vegetation density, on travel rates along wildland firefighter escape routes. When compared to other travel rate models, Campbell et al. (2017) found that slope had less of an effect on travel rate than what was seen using Naismith's Rule, Tobler's Hiking Function, and the modification by Davey et al. (1994). They suggested this was due to their study routes being shorter and in a wildland environment, and the slope on their study routes not exceeding 15°.

54. The follow up study by Campbell et al. (2019) examined the relationship between slope and travel rate using crowdsourced data from the fitness tracker application, Strava. They plotted this data using three widely used probability distribution functions (Laplace (double exponential), Lorentz (also known as Cauchy), and Gauss (normal distribution)) to predict the travel rate on different gradients, looking at the asymmetry on uphill and downhill slopes (Figure 5)(Campbell et al. 2019). They identified the Laplace function as being most suitable for modelling fast travel rates while Lorentz was best for modelling slower travel rates. They also concluded that the Lorentz function was the most appropriate function to use if a single, variable function was desired (Campbell et al. 2019). The original Lorentz function (equation 8) was adjusted (equation 9) to allow easier modelling of the real-world time/slope data:

$$y_{Lorentz} = \frac{1}{\pi b\left[1+\left(\frac{x-a}{b}\right)^2\right]}$$

(8) Unaltered Lorentz/Cauchy function

Where a centres the curve (similar to mean distribution) and b widens the curve (similar to the standard deviation).

$$v_{Lorentz} = c\left(\frac{1}{\pi b\left[1+\left(\frac{\theta-a}{b}\right)^2\right]}\right) + d + e\theta$$

(9) Lorentz Function – Campbell et al. 2019

Where a and b are as in equation 8, c adjusts the data so it is bound by [0,10] instead of [0,1], d ensures the travel rate curve never reaches zero, e allows for the anisotropy of uphill/downhill travel rates, π is calculated to 14 decimal places, and θ is the slope in degrees.

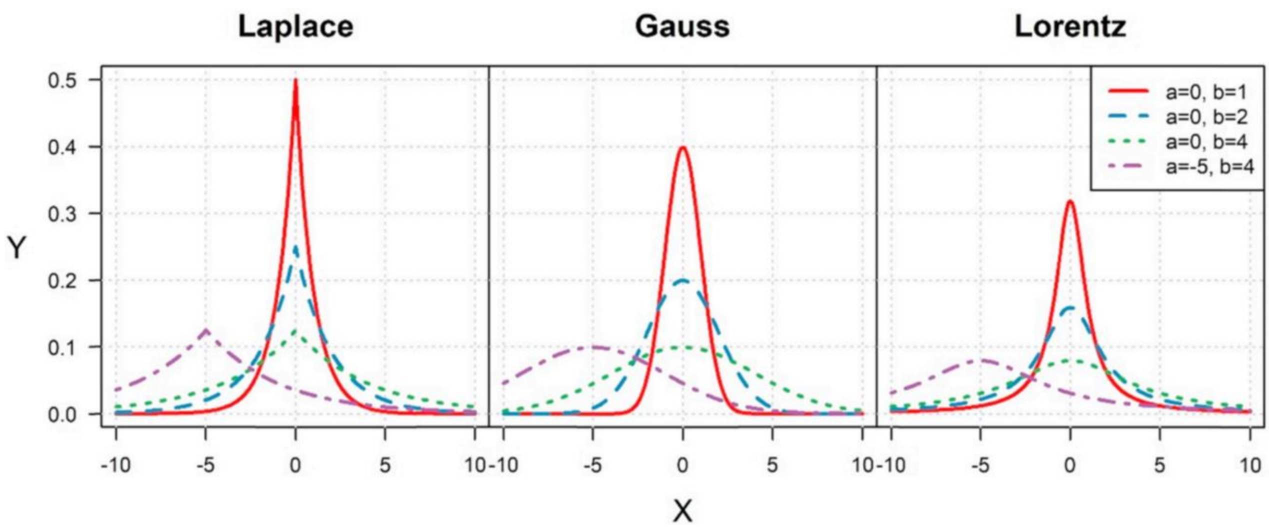

Figure 5: Comparison of Laplace, Gauss, and Lorentz distribution functions, described by Campbell et al. 2019.

55. Doherty et al. (2014) looked at how a walker's demographics and the physical geography of an area (such as surface type and slope) could impact travel distance. They compared these variables using Euclidean distance statistics and a travel-cost mobility model. When the two models were compared, there were significant differences in travel time. They inferred that movement is restricted by terrain; travel time was less variable on flat terrain and more variable with increasing elevation. They concluded the travel-cost mobility model (based on terrain type and human geography) was a more realistic tool for estimating travel time.

56. Maghari-Sáska and Dombay (2012) used a Digital Elevation Model (DEM) to estimate maximum walking distance from a given point on mountainous terrain. They compared the results from two

popular travel rate functions, Naismith's Rule (and its corrections) and Tobler's Hiking Function, using a DEM as the elevation input. They concluded the hiking times from the different models were very similar. They believed the correlation between Naismith's rule and Tobler's rule means corrections applied to Naismith's rule to improve accuracy (such as Tranter's correction) can also be applied to Tobler's Hiking Function.

57. Wood and Schmidtlein (2012) examined how least-cost-distance models responded to varying inputs, such as the resolution of the input data and assumptions made about travel rate in relation to tsunami evacuation. They noted that historically these models have assumed movement is in a straight line and has ignored slope. They aimed to include path-distance, direction of travel, slope, and surface cover in their model calculations. Their results showed that travel time was consistently underestimated when distance was the only variable. Using elevation at a 1m resolution had a significant impact on the model by increasing travel times in evacuation zones.

58. Pingel (2010) described the different variables a walker considers when choosing a route, focusing on slope. They proposed that walkers tend to overestimate slopes when deciding on a route. This overestimation can affect modelling least-time route calculations in mountainous areas. Pingel (2010) developed a model for estimating cost as a function of slope. The model developed by Pingel (2010) calculated the cost associated with travelling across a linear slope and enhanced it using a cost function associated with cognitive research derived from human path finding. The model treated uphill and downhill slopes the same, but Pingel (2010) noted cost should be applied asymmetrically. While a walker's travel rate may be faster when moving downhill on gentler slopes, as the downhill slope gets steeper, travel rate decreases and may become slower than travelling uphill (Pingel 2010).

59. Finnis and Walton (2008) observed pedestrian travel rates, as influenced by gradient and environment, in the field. The measured walking speed at 13 sites in four urban locations in New Zealand: Auckland, Wellington, Palmerston North, and Levin. Multiple characteristics were observed, including commuter gender and age, shoe type, presence of baggage, and slope. Finnis and Watson (2008) observed pedestrian travel rates being faster when travelling downhill than uphill, and slower on the flat slopes versus travelling uphill or downhill. They found travel rate would increase as the gradient increases up to 6° and then decrease. They concluded that New Zealanders have a faster walking travel rate when compared to international studies. This indicates the need for location specific input for travel rate calculations.

60. Kawamura et al. (1991) performed gait analysis on 17 healthy, young men in a controlled environment. They studied the effect slope had on step length, stride width and walking cadence (the number of steps per minute). The results showed walking cadence changed when travelling

uphill, becoming increasingly smaller the steeper the gradient. When travelling downhill, the step length become shorter as the slope became steeper. The work by Sun et al. (1996) supported the findings of Kawamura et al (1991). In analysing the gait of 2400 urban pedestrians as they travelled across an area of naturally varying slope, Sun et al. (1996) concluded that step length shortened when travelling downhill.

4.4. Travel Rate and Age

61. In their draft New Zealand Pedestrian Network Guidance, Waka Kotahi describes a "fit and healthy" adult as walking approximately 5km/h and the low range for an older adult as being 3.3km/h (Waka Kotahi 2021). These differences in pedestrian travel rates from the same source, highlights the variation in the definition of an "average" travel rate (see
62.
63. Table 1).

64. The Pedestrian Planning and Design Guide (Waka Kotahi 2009) is New Zealand's comprehensive official guide to planning and design for walking. It sets out pedestrian travel rates based on various walking behaviour research studies by Daamen and Hoogendoorn (2003), Milazzo et al. (1999), the Florida Pedestrian Planning and Design Handbook (1999) and Knoblauch et al. (1996). The travel rates are broken down into three categories of adults: fit and healthy, average (the majority), and aged or mobility impaired (see
65.
66. Table 1).

Table 1: Walking travel rates defined by Waka Kotahi in their Pedestrian Planning and Design Guide (2009) and New Zealand Pedestrian Network Guidance (2021)

	Fit and healthy		Average		Aged/mobility impaired	
	m/s	km/h	m/s	km/h	m/s	km/h
New Zealand Pedestrian Network Guidance, Waka Kotahi 2021	1.4	5.0	-	-	0.9	3.3
Pedestrian Planning and Design Guide, Waka Kotahi 2009	1.5	5.4	0.8 – 1.8	2.9 – 6.5	1.2	4.3

67. Pinna and Murrau (2018) worked to understand how age affects pedestrian travel rate and to assess a statistical model describing the impact of age on pedestrian behaviour. The results showed younger participants walked, on average, 19.2% faster than older participants, however the effect of age on travel rate was not linear. They summarised other studies which also investigated age as a factor of walking speed (Table 2). Pinna and Murrau (2018) carried out their own study to create a statistical model of the impact of age on pedestrian speed. Pinna and

Murrau did not consider slope in their research so their observations are assumed to be for pedestrians on a flat (0°) slope.

Table 2: Comparison of pedestrian travel rate age brackets from the literature review of Pinna and Murrau (2018).

Willis et al. (2004)	**<16yrs**		**16-25yrs**		**26-50yrs**		**51-64yrs**		**>64yrs**	
	m/s	km/h	m/s	km/h	m/s	km/h	m/s	km/h	m/s	km/h
	1.53	5.5	1.55	5.6	1.47	5.3	1.38	4.9	1.16	4.2
Finnis et al. (2007)			**15-30yrs**		**30-55yrs**		**>55yrs**			
			m/s	km/h	m/s	km/h	m/s	km/h		
			1.46	5.3	1.49	5.4	1.37	4.9		
Nazir et al. (2014)	**Children**		**Young**		**Adults**				**Elderly**	
	m/s	km/h	m/s	km/h	m/s		km/h		m/s	km/h
	1.03	3.7	1.125	4	1.12		4		1.05	3.8
Satish et al. (2014)			**<20yrs**		**20-50yrs**		**>50yrs**			
			m/s	km/h	m/s	km/h	m/s	km/h		
			1.24	4.5	1.2	4.3	0.96	3.5		
Pinna & Murrau (2018)					**19-40yrs**				**>65yrs**	
					m/s	km/h			m/s	km/h
					1.04	3.7			0.84	3

68. Ciolli et al. (2006) examined whether the area a missing person can be found in could be defined based on the maximum speed of the person, physiological variables, and terrain features. Their model estimates walking speed based on the parameters such as track slope, vegetation density, the unevenness of the terrain, the person's physical fitness and energy levels, and visibility at different times of day. The information for these parameters was obtained from literature and field data from previous SAR (Search and Rescue) campaigns. Initial testing showed promising results for people aged 20-30 years old, however the authors believed the model underestimated travel rates for other age groups.

4.5. Review and Comparison

69. This report gathered pedestrian travel rate calculations from a variety of sources in existing literature. Most of these sources looked at pedestrian characteristics (age, fitness level, BMI) and their effect on slope, while others looked at slope in isolation. Table 3 shows that a lot of studies have been based of Naismith's Rule, and its subsequent corrections, and Tobler's Hiking Function. These travel rate functions were developed using small or unknown sample sizes which raises questions around quality and accuracy. During the literature review, the travel rates from each study were grouped by the key variable examined (i.e., slope or age) and compared with each other to identify trends (Table 3). Where a paper did not specify slope, it was assumed

the travel rate function was for movement on a flat slope. There was some variability across the literature when defining age bands. The different age band definitions made a direct comparison between studies difficult. For this reason, the comparison was an approximation.

Table 3: Number of participants in travel rate studies and the models/functions used to calculate travel rate.

Study	Sample size	Variable	Function/Model
Naismith (1892)	1	Slope	Naismith's Rule
Tranter (1965)	Unknown	Fitness	Correction to Naismith's Rule
Aitken (1977)	Theoretical study	Surface type	Correction to Naismith's Rule
Langmuir (1984)	Theoretical study	Slope	Correction to Naismith's Rule
Kawamura et al. (1991)	17	Slope	None used
Tobler (1993)	Unknown (secondary data)	Slope	Tobler's Hiking Function
Davey et al. (1994)	2	Slope	Derived on function
Rees (2004)	Unknown (based on 10 hikes)	Slope	Polynomial travel rate model
Ciolli et. al. (2006)	Theoretical study	Demographics and slope	Developed their own
Finnis and Walton (2008)	1,847	Slope and population	None used
Pingel (2010)	Theoretical study	Slope	Tobler's Hiking Function
Magyari-Sáska and Dombay (2012)	Theoretical study	Slope	Naismith's Rule and Tobler's Hiking Function
Wood and Schmidtlein (2012)	9,889	Slope and terrain cover	Least-cost-pathway
Doherty et al. (2014)	393 SAR incidents	Demographics and slope	Euclidian distance and travel-cost mobility model
Campbell et al. (2017)	31 participants, 62 measurements	Slope	Linear mixed effects regression (LMER) analysis
Irmischer and Clarke (2018)	200	Slope	Gauss curve
Pinna and Murrau (2018)	2,794	Age	Multiple regression
Campbell et al. (2019)	29,928 Strava users providing 421,247 trips	Slope	Laplace, Gauss, and Lorentz
Aghabayk et al. (2021)	1,615	Slope, Age, BMI	Analysis of variance, T-test, and regression analysis

70. The review of the literature showed that the current industry standard is too fast to be considered an average pedestrian travel rate. While some travel rate values for an adult aligned (or in some cases exceeded) the industry standard of 1.38m/s (5km/h), most travel rate values were lower than this. This is particularly true for younger age groups, older age groups, and those with a mobility impairment. The specific travel rate values identified in the literature are further covered in section 5.3.2.

71. The WCC Walking Network Model will be required to calculate walkable catchments for the population in Wellington City. It will have multiple use cases: emergency evacuation planning, community services, urban planning and design, and more. The review also highlighted that a single travel rate calculation would be insufficient for capturing the differences in travel rates across the diverse population of Wellington. It was decided that three calculations would be used to capture different walking speeds and abilities in the Wellington population: low, moderate, and fast travel rates.

5. Methodology

72. Work began on updating the WCC Walking Network Model in November 2020. The goal was to create a trust-worthy, accurate, and dynamic dataset so that teams within WCC would have reliable access to this information. Priority was given to updating the walking network data and calculations due to the need of the District Plan team as part of their District Plan review. The first draft of the updated model was completed in March 2021.

73. The methodology section comprises five parts. First, background context on the Spatial Plan and the District Plan is provided. Second, the process for selecting a function to use in the travel rate model is discussed. Third, the characterising of low, moderate, and fast travel rates using secondary data from the literature review is described. Forth, the Lorentz function variables to use in the Walking Network Model are identified. Fifth, the process of building and configuring the Walking Network Model is detailed.

74. There was significant time pressure to have the model upgrade completed and functional prior to the release of the Officer Recommended Spatial Plan in November 2021. The time pressure was due to the National Policy Statement on Urban Development 2020 (NPS-UD). The NPS-UD required the District Plan team to enable intensification in areas within a walkable distance from centres mass rapid transport (MRT) stations as part of their District Plan review (Ministry for the Environment 2020). Because of this, additional resources were allocated to rebuild the model with updated calculations, following a literature review, and applying readily accessible data.

5.1. Use in the Spatial Plan and District Plan

75. The NPS-UD 2020 sets out the objectives and policies for planning for well-functioning urban environments under the Resource Management Act (RMA) 1991. It replaced the National Policy Statement on Urban Development Capacity 2016 (NPS-UDC) and took effect on 20 August 2020 (Ministry for the Environment 2020).

76. Policy 3(c) of the NPS-UD requires tier 1 councils (such as Wellington City Council) to update their District Plans to enable “building heights of at least 6 stories within at least a walkable catchment of the following:

    i. Existing and planned rapid transit stops,

ii. The edge of city centre zones,

iii. The edge of metropolitan centre zones.” (Ministry for the Environment 2020)

77. The District Plan team required walking catchments be created in line with guidance from the NPS-UD. The NPS-UD defines a walkable catchment as “the area an average person could walk from a specific point to get to multiple destinations” (Ministry for the Environment 2020). A walkable catchment shows where and how far pedestrians can travel from a certain start point in any given direction. The standard for a “walkable distance” is taken as 400m – 800m, approximately 5- to 10-min of walking (Yang & Diex-Roux 2012, Walker 2011, Waka Kotahi n.d., Queensland Government 2018).

78. A catchment can be defined in two ways: using distance (e.g., an 800m radius) or using time (e.g., 10 minutes). WCC chose to use a time-based walkable catchment to create a more accurate, ‘real-world’ result (Table 4). A WCC Walking Network Model for Wellington City was required to generate these walking catchments and identify areas where intensification was required.

Table 4: Timeline of Spatial Plan and District Plan walkable catchments.

	Central City	**Metropolitan Centres**	**Railway Stations**
Draft Spatial Plan*	10 min catchment	10 min catchment	10 min catchment
Pre-Approved Spatial Plan	10 min catchment	10 min catchment	10 min catchment: *Kenepuru, Tawa, Johnsonville* 5 min catchment: *Linden, Redwood, Takapu Rd, Raroa, Khandallah, Box Hill, Simla Crescent, Awarua St, Ngaio, Crofton Downs*
Adopted Spatial Plan	15 min catchment	10 min catchment	10 min catchment
Draft District Plan	15 min catchment	10 min catchment	10 min catchment
Proposed District Plan	10 min catchment	10 min catchment	10 min catchment: *Kenepuru, Tawa* 5 min catchment: *Linden, Redwood, Takapu Rd* (Johnsonville line removed)

*Used old Walking Network Dataset

5.2. Choosing a Function

79. The WCC Walking Network Model needed to produce realistic results for pedestrian travel rates when travelling uphill and downhill, especially given Wellington's hilly topography. The literature review found that most common travel rate calculations overestimate the 'average' pedestrian travel rate, particularly on a flat surface. The functions also tend to exclude pedestrian characteristics (such as age or fitness level) in the calculations.

80. The WCC Walking Network Model needed to be customised to include low, moderate, and fast walking speeds. Customising the model to have a calculation for each speed would enable walkable catchments for pedestrians who are faster or slower than 'average' to be modelled.

81. Based on the literature reviewed, the methodology of Campbell et al. (2019) and Irmischer and Clarke (2018) was determined to be most fit for purpose. Campbell et al. (2019) and Irmischer and Clarke (2018) recommended using a function that generated a distribution curve to model travel rate on sloped surfaces. Irmischer and Clarke (2018) stated that a Gauss curve (normal distribution or a symmetrical bell curve) represented travel rate on uphill and downhill slopes more accurately. Campbell et al. (2019) compared three distribution curves and used data collected from Strava Metro to find the best fit. They found the Laplace function best aligned with moderate to fast walkers and the Lorentz function best aligned with slower walkers. They advised using the Lorentz function if a single function that could be modified easily for different scenarios, was required.

82. Campbell et al. (2019) used data sourced from the fitness application Strava in their analysis, while Irmischer and Clarke (2018) used data collected from US Military cadets. It can be assumed that data from these two sources will not accurately represent the average pedestrian. In addition to this, Strava data did not specify a mode of travel (i.e., running or walking). When Campbell et al. (2019) tested the different distribution functions, they did so by splitting the Strava data into percentiles ranging from slow (1st percentile) to fast (99th percentile). Their categorisation of slow, moderate, and fast were based on these percentiles. When Campbell et al. (2019) recommended using the Laplace function for moderate to fast walkers, this was based on data that was potentially skewed fast. For this reason, this report opted to use the Lorentz function for the travel rate calculations in the WCC Walking Network Model (equation 9).

5.3. Identifying a Wellington-specific Travel Rate

83. Finnis and Walton (2008) measured pedestrian travel rates in different locations in New Zealand to identify different influences on mean travel rates (such as slope, age, and type of footwear).

They noted that there were no New Zealand data on pedestrian travel rate available which caused them to question if current design parameters (using global metrics) were applicable. Having collected data on pedestrian movements in four centres in New Zealand (Wellington, Auckland, Levin, and Palmerston North), Finnis and Walton (2008) had the following conclusions:

- Pedestrians travelled faster downhill than uphill
- Pedestrians travelled faster on a slope (uphill and downhill) than on the flat
- Men walked faster than women
- Younger people walked slightly faster than older people
- Pedestrians in smaller, rural centres walked faster than those in larger population centres
- People in New Zealand have a higher pedestrian travel rate compared to their international counterparts.

84. While Finnis & Walton (2008) examined the effect of the slope on pedestrian travel rate, they did not provide a breakdown of the travel rates and slope values. This makes it difficult to use their data in the WCC Walking Network Model. Their results for the impact of pedestrian age on travel time formed part of the travel rate values specific to Wellington in the WCC Walking Network Model.

85. In order to identify a pedestrian travel rate that was specific to the Wellington population, data was collected and analysed from Strava Metro. Knowing there are caveats to this (mainly not knowing the travel mode), data was also collected from WCC Officers who were known to be walking. This enabled 'walking' travel rates from the Strava Metro data to be identified. By comparing the Strava Metro data, the WCC Officer data, and data used in Campbell et al. (2019), low, moderate, and fast travel rate categories were defined.

5.3.1. Collecting Data with Strava

86. Strava is a GPS dependent, online service used to track physical activity. Users download the Strava application on their mobile phones or GPS-enabled device and record their activities from a list of supported activity types such as running, walking, bike riding, and hiking. These activities can be shared to the user's followers or publicly, and other users can comment on them or give "kudos" (Strava 2023).

87. Depending on the activity selected, the app records and shows the user's activity results such as a route summary in a map view, elevation (net and unidirectional), speed (average, max/min) and timing (total and moving time) (Wikipedia 2020).

88. Strava was used in three ways in this study: 1) identifying travel rate patterns, 2) identifying travel rate percentiles appropriate for low, moderate, and fast pedestrians, and 3) testing travel rate calculations. The GPS data provided by Strava allows the activity to be mapped spatially and analysed for travel rate and slope travelled. Because of its large user base, Strava data is ideal for looking at human movement patterns (Figure 66).

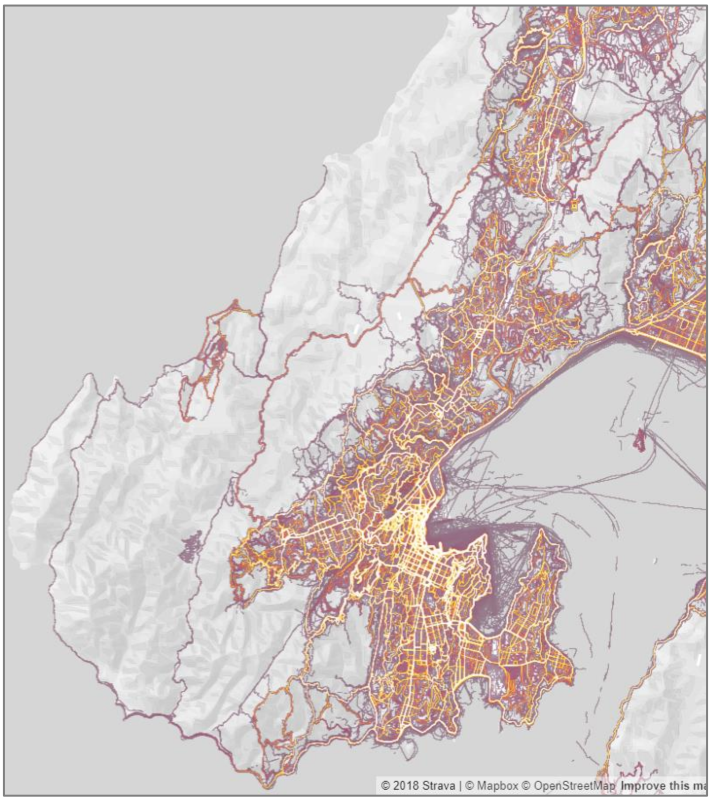

Figure 6: Heat map of aggregated trips in Wellington, recorded on Strava over the past two years (Strava, 2018). Captured March 2021.

89. Strava have set up a service called Strava Metro which aims to help planners and transportation specialists to improve city infrastructure for cyclists, runners, and walkers (Strava 2020a). The data accessed through Strava Metro follows the European Union's General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) guidelines. This means it has been aggregated and identifiable information has been removed, making it anonymous. After applying for access to Strava Metro, this aggregated user data can be downloaded in bulk and analysed to find patterns. The "activity type" attribute in the downloaded data is classified as "run" by default, even though the data includes run, walk, and hike modes of transport. Table 5 below lists the advantages and disadvantages of using this anonymous Strava Metro data in our analysis:

Table 5: Comparing the advantages and disadvantages of using Strava data for testing the Walking Network Model.

Advantages	**Disadvantages**
Allows the collection of large-scale, objective GPS data on the activity location (Hirsch et al. 2014).	As Strava is a fitness tracking app, it can be assumed its users are fitness conscious. This may not be representative of the general population (Hirsch et al. 2014).
GPS data are more accurate than self-reported activity diaries and travel surveys where an individual's location is recorded (Maddison & Mhurchu 2009).	Because Strava is primarily a smart phone app, it's users may be younger. Most users seem to be between the ages of 25 and 44 (Lissner et al. 2018). Figure 7 shows the age distribution of Strava users and Figure 8 shows the age/sex population pyramid for Wellington City.
Collecting the data on a mobile phone app reduces the burden on the participant to carry a separate GPS device to record their activity (Hirsch et al. 2014).	Compared to Census data, Strava users are more likely to be male (Lissner et al. 2018).
The Strava app is free to download and available across multiple devices and systems (Hirsch et al. 2014).	
Strava has over 60 million members around the world and includes people from a range of ages and backgrounds (Strava 2020a).	
In 2020, Strava users have recorded a total of 3 billion activities since its founding in 2009. This means it is a wealth of fitness activity data (Strava 2020b).	

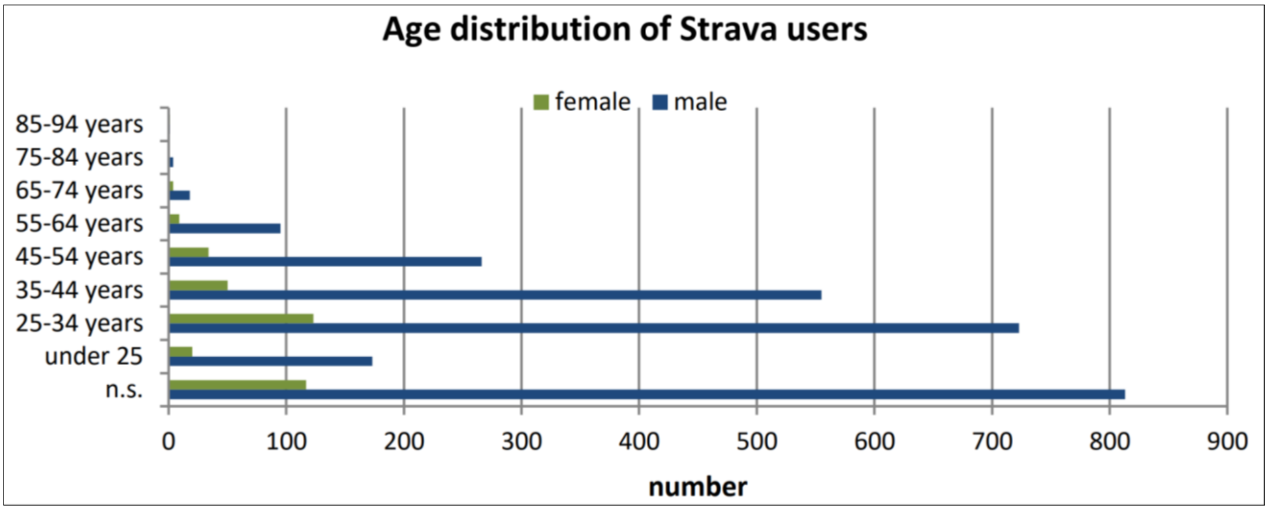

Figure 7: "Distribution of age and gender of Strava users in the city of Dresden" (Lissner et al. 2018) where "n.s." is "not specified".

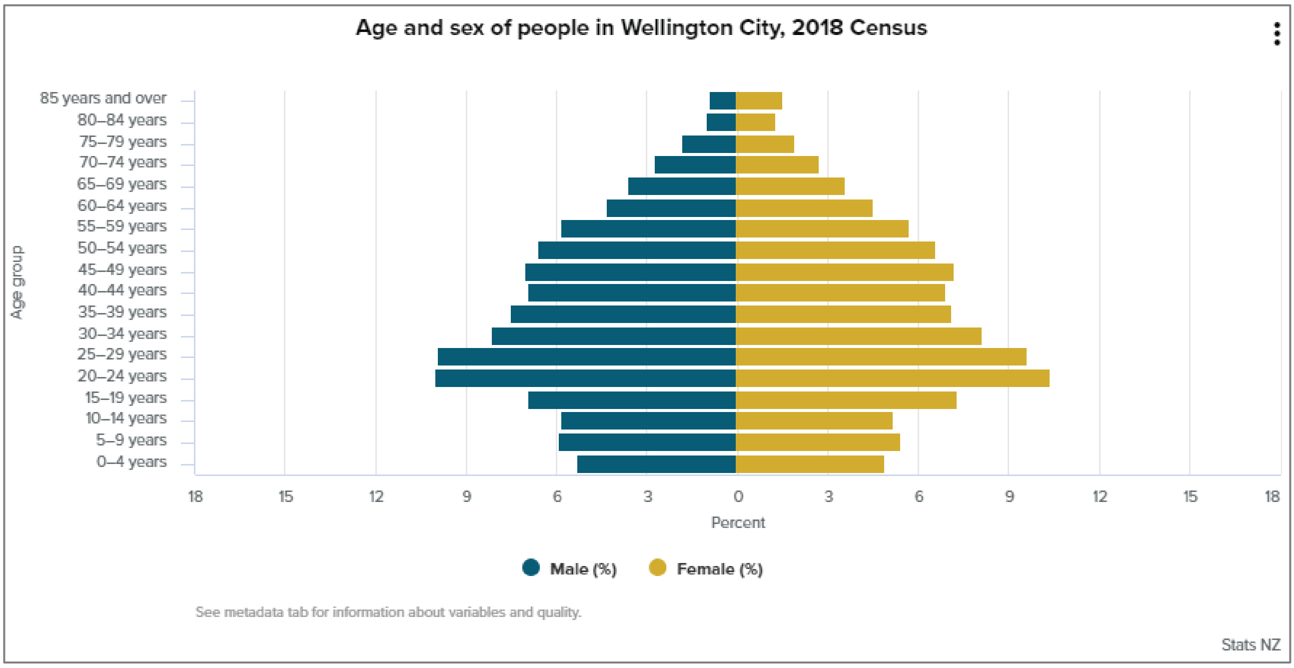

Figure 8: Population pyramid for Wellington City, by age and sex, for 2018 (StatsNZ, 2018).

90. As well as collecting generalised bulk data from Strava, data was collected from WCC Officers. Users recorded any walking they did using the Strava application over a two-week period. While this sample size was significantly smaller than the Strava Metro dataset, it had the benefit of 1) being a known activity type (walking) and 2) being at an individual trip level and not aggregated.

5.3.2. Defining Low, Moderate, and Fast Travel Rate Categories

91. The values from the Strava Metro data were plotted on a travel rate (m/s) versus slope (in degrees) scatter graph (Figure 9). It was not possible to differentiate between uphill and downhill in the Strava data, so slope values were grouped and represented as positive values (travelling uphill). This prevented the distribution curves seen in Campbell et al. (2019) and Irsmicher & Clarke (2018) being observed in the data. This meant the asymmetry in the distribution of travel rate versus slope could not be observed in the Strava Metro data, and some additional work would need to be done to extract travel rates for different slope values.

92. The Strava Metro data and data collected from WCC Officers was grouped into 1st to 99th percentiles. These percentiles would allow for comparison between the Wellington-specific data and the data gathered from the literature review. Being able to compare the data would enable the categorisation of low, moderate, and fast travel rates. Figure 9 shows a scatter plot of the Strava Metro data (black dots) and the WCC Officer data (red dots). The difference in travel rate between the Strava Metro data (where mode of travel was unknown but assumed to be mostly running) and the WCC Officer data (where the travel rate was known to be walking), confirmed

the assumption that the Strava Metro data skewed fast. The 1st to 99th percentiles for the Strava Metro data were also plotted with a trendline for the average WCC Officer travel rate. Comparing the WCC Officer average trendline with the Strava Metro percentiles indicated which percentiles were more likely to represent users who were walking (percentiles 1 to 10) versus running (percentiles 15 and higher). This would be valuable information for calculating the Lorentz function variables using the Strava data from Campbell et al. (2019).

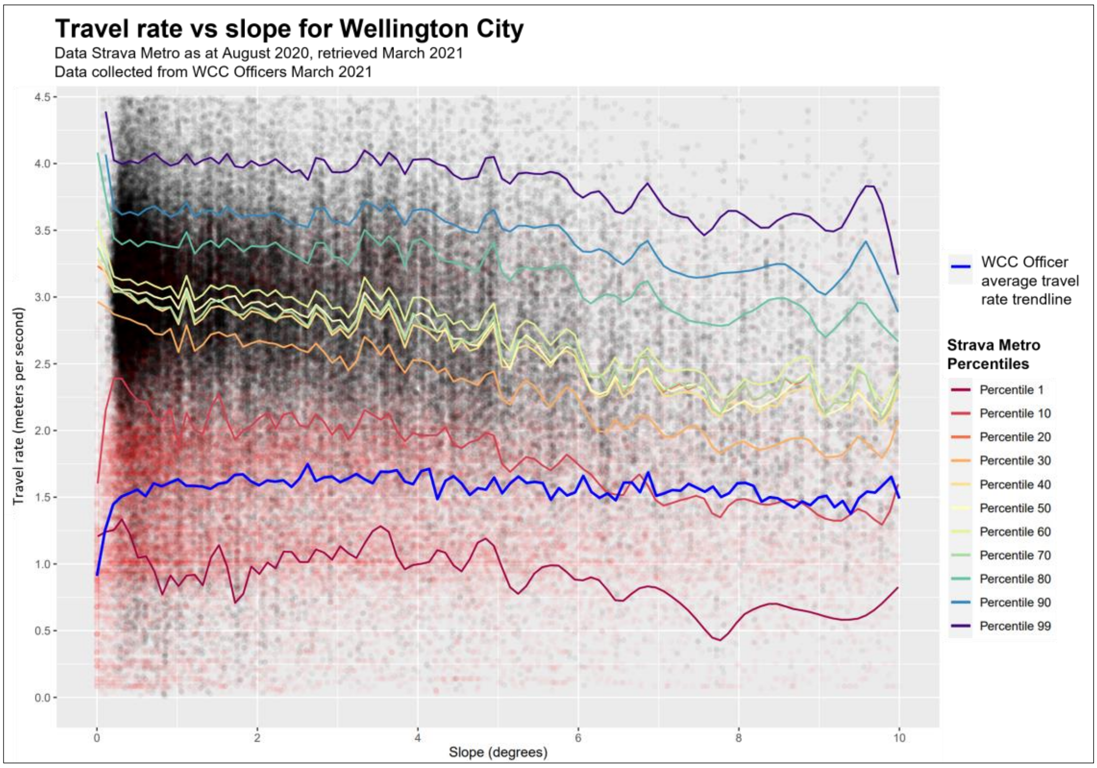

Figure 9: Scatter graph of the Strava Metro data (black dots) and WCC Officer data (red dots). Strava Metro data has been split into percentiles 1 - 99. A trend line for the WCC Officer data is shown in blue.

93. To compare the Strava Metro data and the WCC Officer data with the travel rate data collected from the literature review, the Campbell et al. (2019) data slope values were aggregated to remove the uphill/downhill directionality. The literature review values were colour coded based on the pedestrian characteristics they represented (Table 6). Travel rates that were slower than the industry standard (5km/h) were labelled 'Below average' while those faster than the industry standard were labelled 'Above average'. There was some variation in how the studies that examined age grouped their age bands, therefore the grouping of these studies was very broad.

94. Based on the literature review, study travel rates for adults considered fit and healthy, which had participants aged between 21 years and 54 years, or did not specify any details, were labelled as 'Average'. Study travel rates for participants aged 20 years old or younger were labelled as 'Children/Youth', while study travel rates for participants aged 55 years or older, or had participants who were mobility impaired, were labelled as 'Older/Mobility impaired' (Table 6).

Table 6: Pedestrian characteristic groupings derived from the literature review.

Category	Description
Below Average	Slower than 5km/h
Above Average	Faster than 5kn/h
Average	An “average”, fit/healthy adult
Children/Youth	Aged 20 years or less
Older/Mobility impaired	Aged 55 years or more or mobility impaired

95. Where a study included information about slope, it was grouped under the travel rate percentiles for flat, 10 degrees, or 15 degrees. If a study did not mention slope, it was assumed the travel rate was calculated on a flat surface. If the travel rate did not align with any of the percentiles, it was not included in the table.

96. The literature review categories were grouped under the Strava Metro (Figure 10) and WCC Officer (Figure 11) percentiles/travel rates they were closest to. This comparison helped identify any alignment between the travel rates identified in the literature, and their associated categories, and the travel rate percentiles that would form the basis of the Walking Network Model calculations. For example, many categories classified as ‘Average’ or ‘Above Average’ aligned with percentiles 1 to 10 of the Strava Metro data. This suggested that while the Strava Metro data probable represented ‘walking’ at those percentiles, it was quite a fast travel rate as the same categories aligned with the higher percentiles (30 and 40) for the WCC Officer data. Similarly, categories for ‘Below Average’, ‘Children/Youth’, and ‘Older/Mobility impaired’ aligned with the lower WCC Officer data percentiles (5 to 20), while the Strava Metro data rarely aligned with these categories. Using the percentiles and the pedestrian characteristic groupings, travel rate values for the low, moderate, and fast calculations were identified (Figure 11).

	Below average
	Above average
	Average
	Children/Youth
	Older/Mobility impared

Strava Metro - Wellington City

Flat slope				
Percentile	1	5	10	15
m/s	1.219	1.374	1.602	2.317
	Ciolli et al. (2006)	Naismith's Rule	Campbell et al. (2019)	
	Knoblauch et al. (1996)(Ages 14-64)	Tobler's hiking funciton	Waka Kotahi (Average)	
	Milazzo et al. (2007)(Ages 14-64)	Willis et al. (2004)(Aged 51-64)*		
	Satish et al. (2014)(Aged <20)*	Finnis et al. (2007)(Aged >55)*		
	Satish et al. (2014)(Aged 20-50)*	Waka Kotahi (Fit adult)		
	Waka Kotahi (2021)(Mobility impared)	Campbell et al. (2019)(Laplace 10th percentile)		
		Campbell et al. (2019)(Lorentz 10th percentile)		

* Sourced from the Pinna & Murrau (2018) literature review

10 degree slope				
Percentile	1	5	10	15
m/s	0.826	1.140	1.598	1.759
	Irmischer & Clarke (2018)		Campbell et al. (2019)	
	Campbell et al. (2019) (Lorentz 5th/10th percentile)			

Figure 10: Travel rate comparison between Strava Metro data for Wellington City and the literature review data categories.

WCC Officer Strava Data

Flat slope						
		Low		Moderate		Fast
Percentile	5	10	15	20	30	40
m/s	0.608	0.888	0.985	1.064	1.206	1.358
		Pinna & Murrau (2018)(0.84m/s)	Pinna & Murrau (2018)(0.99m/s)	Irmischer & Clarke (2018)(1.1m/s)	Ciolli et al. (2006)(1.25m/s)	Naismith's Rule (1.33m/s)
		Waka Kotahi (0.8-1.8m/s)	Knoblauch et al. (1996)(0.97m/s)	Pinna & Murrau (2018)(1.04m/s)	Knoblauch et al. (1996)(1.25m/s)	Tobler's hiking function (1.38m/s)
			Satish et al. (2014)(0.96m/s)*	Pinna & Murrau (2018)(1.0m/s)	Satish et al. (2014)(1.24m/s)*	Willis (2004)(1.38m/s)*
			Waka Kotahi (0.8-1.8m/s)	Willis (2004)(1.16m/s)*	Satish et al. (2014)(1.2m/s)*	Finnis (2007)(1.37m/s)*
			Wood & Schmidlein (2012)(0.9m/s)	Nazir (2014)(1.03m/s)*	Waka Kotahi (1.2m/s)	Waka Kotahi (0.8-1.8m/s)
				Nazir (2014)(1.05m/s)*	Waka Kotahi (0.8-1.8m/s)	Waka Kotahi (Fit/healthy 1.3-1.5m/s)
				Waka Kotahi (0.8-1.8m/s)	Wood & Schmidlein (2012) (1.2m/s)	

* Sourced from the Pinna & Murrau (2018) literature review

10 degree slope						
		Low		Moderate		Fast
Percentile	5	10	15	20	30	40
m/s	0.474	0.762	0.866	0.921	1.070	1.245
		Campbell et al. (2019) (Laplace 5th percentile)	Irmischer & Clarke (2018) (Down hill 1.03m/s)	Campbell et al. (2019) (Laplace 10th percentile)	Irmischer & Clarke (2018) (Uphill 1.03m/s)	
		Campbell et al. (2019) (Lorentz 5th percentile)		Campbell et al. (2019) (Lorentz 10th percentile)		

20 degree slope						
		Low		Moderate		Fast
Percentile	5	10	15	20	30	40
m/s	0.396	0.578	0.735	0.843	0.982	1.110
	Campbell et al. (2019) (Laplace 5th percentile)	Irmischer & Clarke (2018)				Campbell et al. (2019)
	Campbell et al. (2019) (Lorentz 1st percentile)	Campbell et al. (2019) (Lorentz 5th percentile)				

Below average
Above average
Average
Children/Youth
Older/Mobility impared

Figure 11: Travel rate comparison between WCC Officer data and the literature review data categories.

5.4. Calculating the variables for the Lorentz function

97. The aim of this report was to identify an equation that could be used in the WCC Walking Network Model to calculate travel rates for all line segments, in any direction (i.e., walking towards or away from a starting point, uphill or downhill). It was decided to use the altered Lorentz function derived in Campbell et al. (2019).

98. This function allows travel rates to be calculated dynamically each time the model is run. This adds a layer of transparency to the model as the exact calculation creating the value is stored, rather than a static figure. Not having the travel rates hard coded in the model makes it easier for the model to be updated when there are changes to the network, thus futureproofing it.

5.4.1. Preparing the data

99. When Campbell et al. (2019) were mapping their data with the Lorentz function, the travel rates for moving uphill and downhill were known. The information was not available in the Strava Metro or WCC Officer data. The only travel rate value that was known for certain was for movement on a flat slope (0°). Knowing that the travel rate varied asymmetrically when travelling uphill or downhill, the degree of difference due to the direction of travel needed to be derived from the available data.

100. A table of the WCC Officer data was created where the travel rates values were identical for each direction of travel on the slope. The Campbell et al. (2019) data was plotted using the altered Lorentz function and the WCC Officer data was plotted against it (Figure 12). The two datasets were compared to identify percentiles that aligned with each other (Table 7).

Table 7: WCC Officer travel rate percentiles aligned with Campbell et al. (2019) travel rates plotted using the Lorentz function, grouped into low, moderate, and fast travel rate categories.

	Campbell et al. (2019) Lorentz Plot	WCC Officer Data
Low	1st percentile	10th & 15th percentile
Moderate	5th percentile	20th & 30th percentile
Fast	10th percentile	40th percentile

101. Using the WCC Officer data, the travel rates for the percentiles defining the low, moderate, and fast travel rate categories were averaged together to get a single value. For example, the travel rate values for the 10th (0.888m/s) and 15th (0.985m/s) percentiles on a flat slope were averaged together to get a single value (0.9365m/s) representing the travel rate of a low-speed walker on a flat slope. This was done for the low and moderate travel rate categories for the 0°, 10°, 15°, and 20° slopes without specifying the direction of travel.

102. The average travel rate for the Campbell et al. (2019) data was calculated using the positive (uphill) and negative (downhill) travel times for each slope. The difference between the actual travel rate and the average travel rate for the Campbell et al. (2019) data was calculated for each direction of travel (uphill and downhill) for each slope. This adjustment was then proportionately

applied to the WCC Officer data to get the different travel rates for travelling in each direction on the slopes.

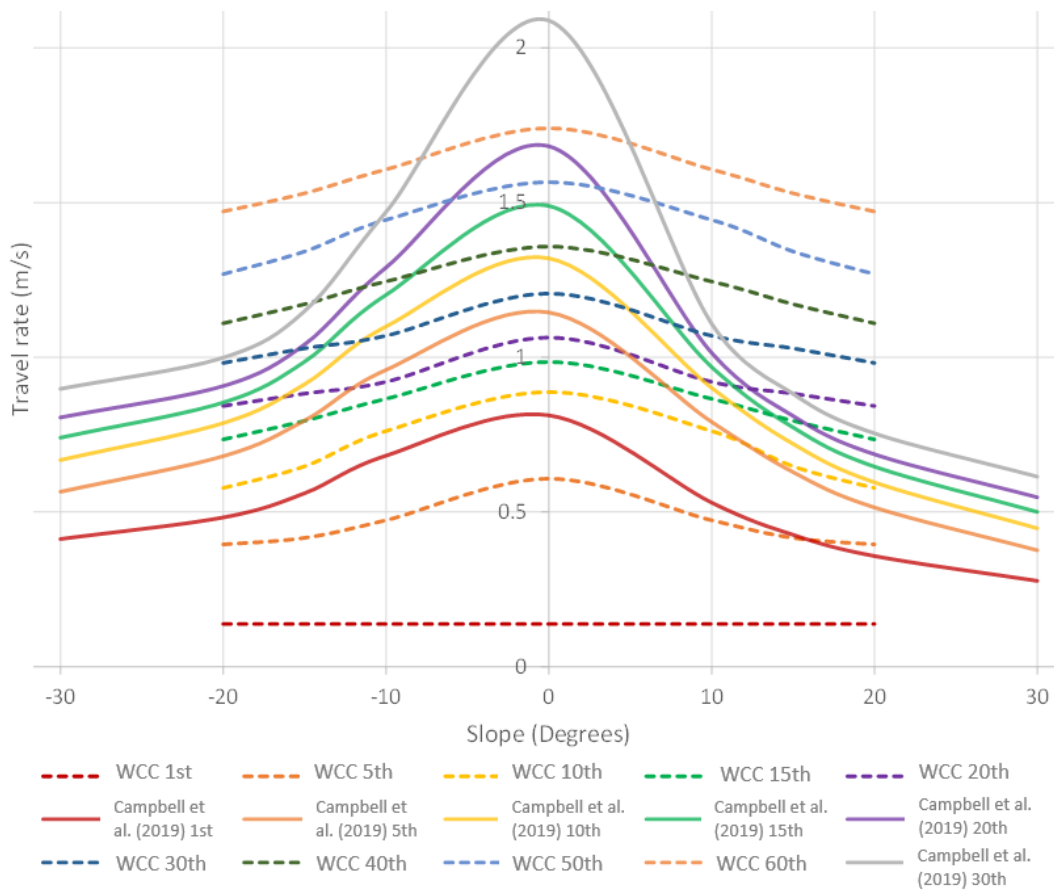

Figure 12: Campbell et al. (2019) and WCC Officer data - travel rate vs slope.

5.4.2. The Lorentzian/Cauchy curve fitting method

103. Curve fitting means creating a curve, or mathematical function, that best matches a series of data points (Wikipedia 2004). The fitted curve can be used for data visualisation to determine values of a function where no data are available, or to summarise relationships between variables (Edmerls 2019). The curve fitting method was necessary for using the Lorentzian function to calculate pedestrian travel rate on slopes. While an average travel rate on a slope was known from the WCC Officer data, the direction of travel was not known. Using the Lorentz function meant there were additional unknown variables. The curve fitting method populated these unknown variables so the function could be added to the network model.

104. The curve fitting method was performed in Microsoft Excel. The altered Lorentz function (Campbell et al. 2019) was reformatted so it could be used both in Excel and in the Walking Network Model:

$$((c) * (1/(\pi * (b) * (1 + ((\theta - (a))/(b))^{\wedge}(2)))) + (d) + (e) * \theta$$

(10) Altered Lorentz function reformatted for Microsoft Excel

Where: a dictates the slope of the highest travel rate/how off centre the curve is

b dictates the width of the curve

c is the impact slope has on faster travel rates versus slower travel rates

d ensures the curve never hits zero

e defines how asymmetrical the curve is

π is calculated to 14 decimal places

θ is the slope in degrees

105. The Campbell et al. (2019) data was plotted to get the base input values for the formula and to create the curve the WCC Officer data could be 'matched' to. Using the Lorentzian/Cauchy curve fitting method described by Edmerls (2019):

- The WCC Officer data was plotted against the Lorentz curve,
- The WCC Officer data 'fit' values and chi squared values (the square of the difference between the Y value in the existing data and the calculated 'fit' value) were calculated, and
- The input values were adjusted manually and using the MS Excel 'Solver Add-in' (Microsoft 2021) until the sum of chi squared was as close to zero as possible (i.e., the curve fit as closely as possible).

106. These steps were repeated for each travel rate: low, moderate, and fast. The input variables calculated using the Lorentzian/Cauchy curve fitting method (Figure 13) were then inputted into the adjusted Lorentz function on the WCC Walking Network Model. The variable for slope (θ) was left as a 'free' variable. This will allow the travel rate for the slope of each line segment to be calculated dynamically each time the model is run.

X	Y (WCC 10th -15th percentiles adjusted)	Y (WCC fit)	WCC chi squared	Campbell et al. 1st percentile	Campbell et al. chi sq
-30	0.644758609	0.652867016	6.57463E-05	0.412636717	0.053880572
-20	0.75397623	0.744134043	9.68686E-05	0.482534506	0.07368061
-15	0.81969368	0.8211041	1.98928E-06	0.56077316	0.067039836
-10	0.915824464	0.90729768	7.2706E-05	0.682357032	0.054507042
0	0.9365	0.938774347	5.17266E-06	0.812720521	0.032961141
10	0.712175536	0.728049578	0.000251985	0.530623503	0.038764379
15	0.62330632	0.625808053	6.25867E-06	0.426419604	0.04050405
20	0.55902377	0.545379733	0.00018616	0.35776759	0.024326481
30	0.433232169	0.435075332	3.39725E-06	0.27726268	
			Campbell et al.	WCC	
	C or 1	I	21.816	30.24297495	
	How off-centre the curve is	A	-2.1	-3	
	b	gamma	12.273	17.43432277	
	Make sure curve never hits 0	d	0.263	0.402487708	
	How asymmetrical the curve is	e	-0.00193	-0.00293	
		sum chi sq	0.385664111	0.0006903	

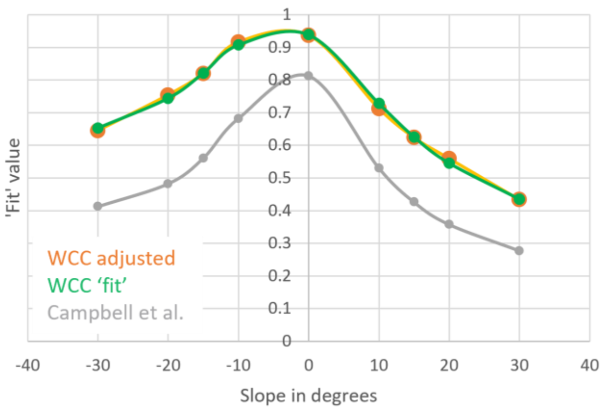

Figure 13: The Lorentzian/Cauchy curve fitting method applied to the WCC Officer data for the low travel rate category.

107. The differences in values between the Campbell et al. (2019) data and the WCC Officer data is due to the data source and the percentiles chosen for each travel rate category. As stated previously, the Campbell et al. (2019) data was sourced from Strava Metro where the travel mode is unspecified. The WCC Officer data was collected specifically for this project and is known to represent pedestrian travel rates. The analysis between the Strava Metro data for Wellington City and the WCC Officer data showed the Strava Metro travel rates tended to be more closely aligned with a runner rather than a walker. It was difficult to get an exact alignment between the Campbell et al. (2019) percentiles and the WCC Officer percentiles. Figure 13 shows the best match for the low travel rate category where the 1st Campbell et al. (2019) percentile was slower than those identified as low in the WCC Officer data, but a higher percentile would have been too fast.

5.5. Building and Configuring the Walking Network Dataset

108. Creating a walking network for Wellington City was a cross-council project and included input from the City Insights GIS Team, City Transport & Infrastructure, Community Services, Parks, Sport and Recreation, Corporate GIS, and many others. The Walking Network Model was built using ArcGIS Pro (Esri 2021) and the Network Analyst toolbox (Esri 2022b).

109. The updated network dataset included:

- Path (updated from the 2010 model), tracks (updated from the 2010), and popular routes through parks (newly added)
- Pedestrian tunnels and bridges (updated from the 2010 model)
- Controlled crossing points with an average wait time (updated from the 2010 model)
- Uncontrolled crossing points with an average wait time (updated from the 2010 model)
- Slope gradient (using an updated 2020 1m Digital Elevation Model (DEM))
- Updated travel rate calculations.

110. Updating the previous Walking Network Model was an arduous process consisting of multiple manual data preparation steps to create the network dataset before the model could be built. This resulted in a time-heavy process that meant the model was not updated for large periods of time. An aim of this model upgrade was to automate the update process as much as possible to allow for more frequent updates taking up fewer resources. Figure 14, below, describes the process, highlighting the automated data preparation processes in purple, and the manual testing and model building in orange.

111. Once the “Create Network Dataset” tool had been run (Esri 2022c), and the walking network dataset had been created, the calculations for the different pedestrian travel rate models could be configured, and the network model could be built (Esri 2022d). Travel attributes were applied to the network parameters. Travel modes (low/moderate/fast) and costs (time calculated by the altered Lorentz function) were defined for each walking speed. The values for the variables a, b, d, e, and π were hard coded using the values derived from the Lorentzian/Cauchy curve fitting exercise. The values for c were input dynamically from the slope degree field in the network attribute table. This was repeated for each travel direction (uphill and downhill) and each travel mode (low/moderate/fast). Where a line in the network was identified as a controlled crossing, an additional cost of wait time was added. This was added dynamically using the wait times in the network attribute table.

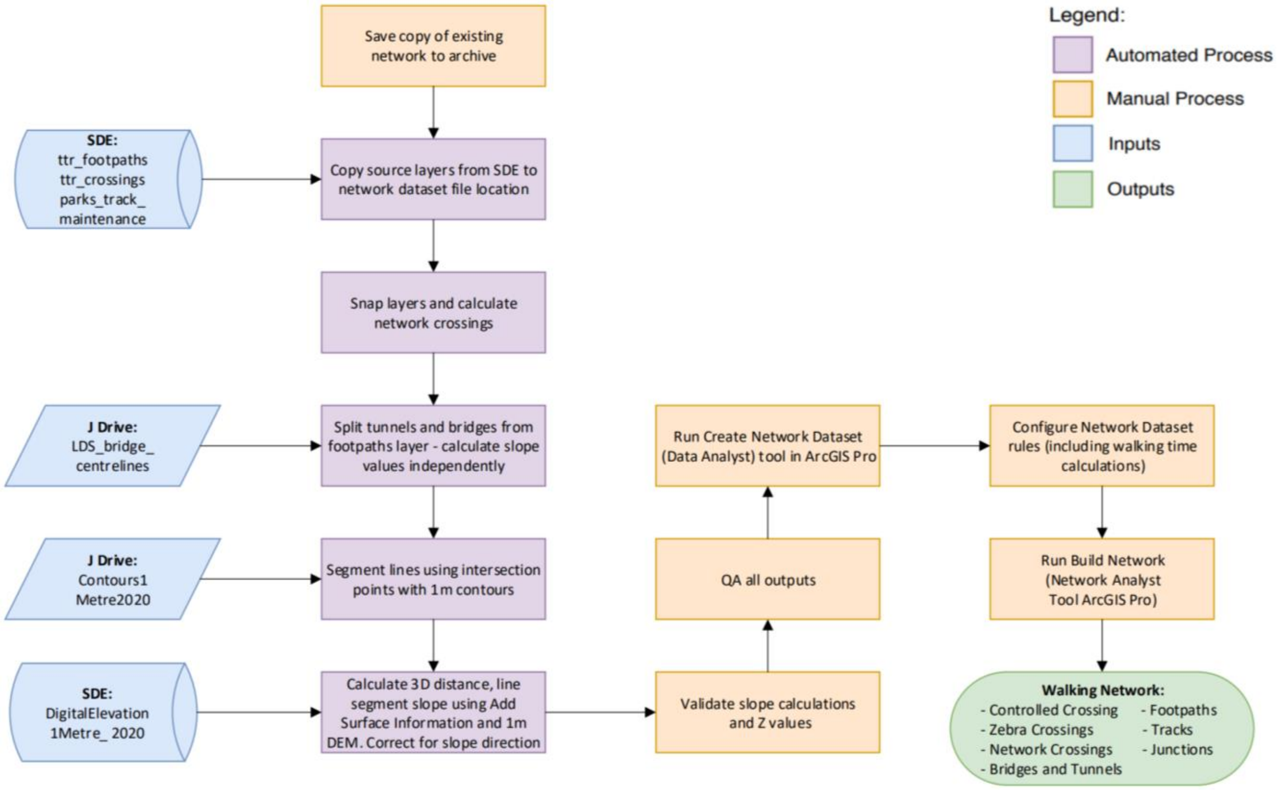

Figure 14: Diagram summarising the steps taken to prepare the data and build the network dataset for WCC's Walking Network Model.

6. Testing the Walking Network Model

112. Testing the Walking Network Model was divided into two streams: testing the model functionality and testing the model output. We engaged with expert GIS users across Council to help us test the draft version of the walking network dataset and model, and provide feedback on:

- The integrity of the network dataset – Identify any gaps in the network and areas where there was a connectivity issue. Testers were asked to examine parts of Wellington they were personally familiar with such as their home suburb or an area of the city they visit often. Where a tester found gaps in the network, or routes that were known to connect in the real work but were not connected in the dataset, the source data for the model was updated.

- The model output – Testers were asked to generate output from the model using the default parameters and review if the output was as expected.
- General functionality – Testers followed instructions on how to use the model and provided feedback on usability. They were also asked to change the input parameters, e.g., to test a scenario relevant to their team, and review the results.

113. When providing their feedback, the testers were asked to consider the following questions:

- Does the output look realistic? Is it consistent with how people move in the real world?
- Reviewing the output, are streets, tracks, or path connections used that appear incorrect or impossible in real life?
- Reviewing the output, are streets, tracks, or path connections *not* used, avoided, or missing from the network data, that would result in a different output?
- If you adjust the parameters of your analysis, does the output change in the way you would expect?

6.1. On the Ground Test Case: Johnsonville

114. During the 24 June Committee meeting, a resolution was passed for WCC Officers to prepare additional evidence to support the 10-minute walking catchments applied in Johnsonville, particularly where it extends beyond that approved for the Medium Density Residential Area in the operative District Plan. Testing was carried out in key locations near the Johnsonville Triangle. This area covers from Kitchener Terrace and Haumia Street in the south, Chesterton Street to the east, Burdendale Grove to the north, and the beginning of Cortina Avenue to the west (Figure 15).

115. Of the anonymised Strava data used to develop the travel rate model, 302km of movements were recorded within the Johnsonville area. In addition to Strava data, 5km of walking calculation testing by WCC staff was also completed. In July 2021, WCC Officers conducted a further 17.8km of walking network catchment testing in Johnsonville to collect additional evidence of the walking network calculations. This additional testing focused on the areas surrounding Middleton Road, Broderick Road, Woodland Road (via Frankmoore Avenue), Sheridan Terrace (via Disraeli Street underpass), and Dominion Park Street (via Fraser Avenue).

116. The WCC Officer tested the 10-minute walking catchment generated from locations identified by the NPS-UD 2020: the boundary of the Johnsonville metropolitan centre area, Johnsonville railway station, and Raroa railway station. The catchment had been created by running the walking network model four times: towards and away from the metropolitan centre using the low and moderate travel rate categories. This generated four catchments which were then averaged together to create a generalised 10-minute walkable catchment (Figure 15). This process was repeated for the Johnsonville railway station and the Raroa railway station.

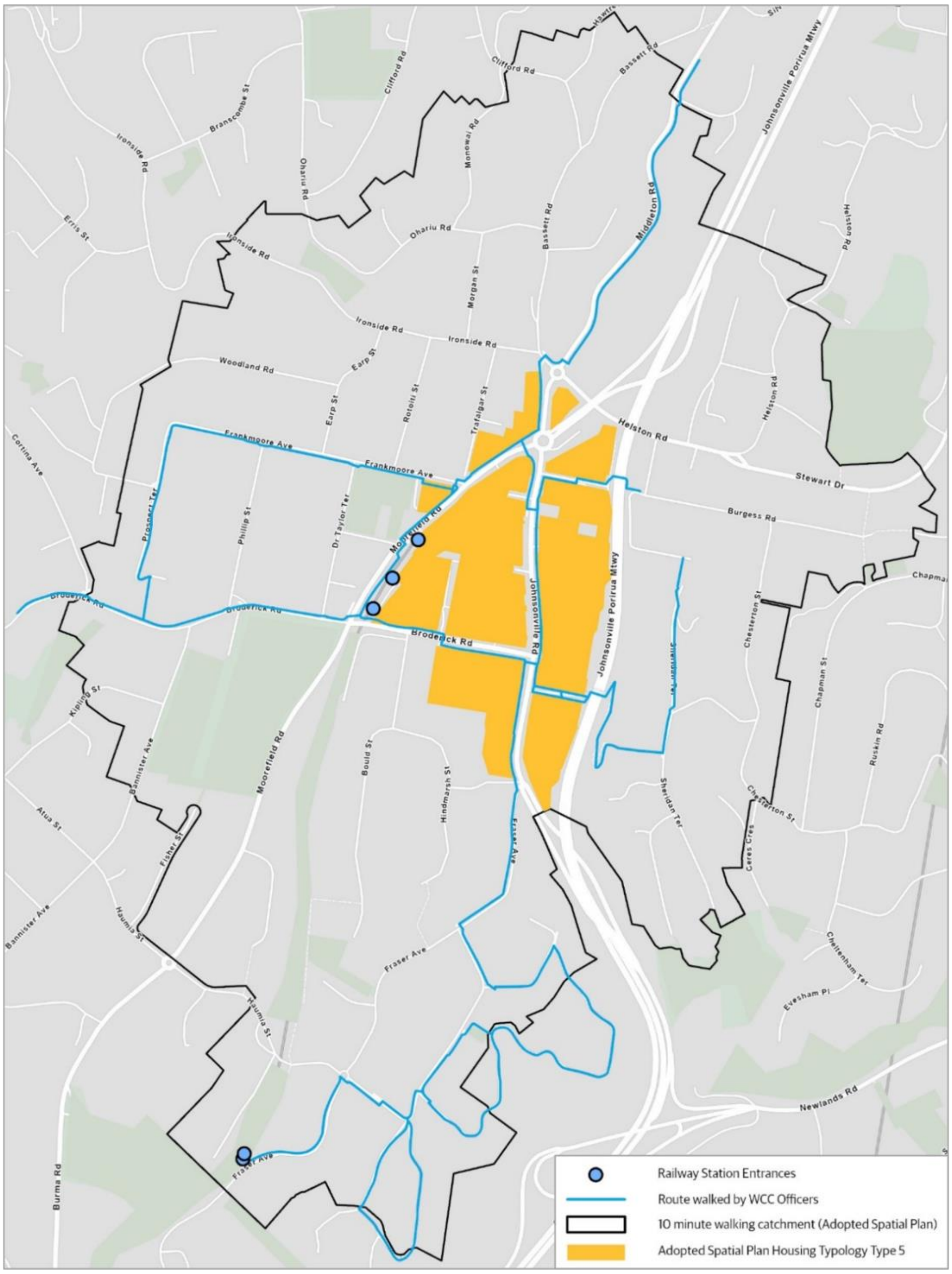

Figure 15: Map of Johnsonville walkable catchments and WCC Officer testing routes.

117. This area had come under scrutiny in the past. There had been concern about the "walkability" of some areas included in the catchment:

- The lack of pedestrian infrastructure at the crossing point on Middleton Road. This infrastructure has since been installed.
- Accessibility of the steps/gradient on Sheridan Terrace (via the Disraeli Street underpass). This area was accessed by a heavily pregnant WCC Officer during testing. The NPS-UD 2020 does not state that accessibility needs to be a consideration for the walkable catchments. Accessibility was not built into this iteration of the model, however, there are plans to incorporate this in future upgrades.

118. Table 8 shows the results of the walkable catchment testing in Johnsonville. The WCC Officers walked 17.8km of the network, testing the 10-minute walkable catchment in 5 different directions. For each test route, the officers reached the catchment boundary in less than 10-minutes. This supported the results of the calculations used by the WCC Walking Network Model.

Table 8: Results of Johnsonville walkable catchment testing by WCC Officers (July 2021).

Johnsonville Walkable Catchment Testing	Distance (km)	Elevation Change (m)	Average Pace (m/s)	Average Walking Time (mins)
Middleton Rd	0.65	28.5	1.339	**8.267**
Broderick Rd	0.60	11	1.345	**7.617**
Woodland Rd (via Frankmoore Ave)	0.57	46	1.25	**8.97**
Sheridan Tce (via Disraeli St underpass)	0.65	51.5	1.115	**9.961**
Dominion Park Street (via Fraser Ave)	0.63	37	1.04	**9.97**

7. Conclusion

119. The purpose of this report was to review pedestrian travel rate calculations and models available in the current literature and identify the most suitable approach for developing a Walking Network Model for Wellington City. The goal was to create a trust-worthy, accurate, and dynamic walking network dataset for Wellington City that:

- is appropriate for Wellington City's hilly topography, and
- can be applied to the population of Wellington City to model walking in 'real-world' conditions.

120. The literature review indicated that the industry standard travel rate of 5km/h was too fact to accurately model walking catchments for the average person. It was decided that a Wellington-specific travel rate needed to be calculated. Following similar methodology by Campbell et al. (2019), activity data from Strava Metro was collected and split into percentiles. To identify which percentiles represented walking, WCC Officers tracked their movements for two weeks, also using the Strava application. Travel rate percentiles from the Strava Metro data and the WCC Officer data were compared with travel rate values gathered during the literature review. This comparison helped identify the WCC Officer travel rate percentiles that represented low, moderate, and fast walking speeds.

121. Campbell et al. (2019) recommended using the Lorentz function for modelling travel rate for lower walking speeds, and if a single, variable function was desired. Using data from Campbell et al. (2019) and the WCC Officer data, variables needed to plot the Lorentz function were identified and built into the calculations that would be used by the WCC Walking Network Model.

7.1 Caveats and Future Work

122. As previously noted, there are caveats with using the Strava data for travel rate analysis. The most notable of these caveats are:

- Strava Metro data assigns running as the default activity
- Strava doesn't provide direction of travel to the data, so it is unknown if the user is travelling uphill or downhill
- Strava Metro data is biased towards their younger user base (aged 25 – 44 years)
- Being a fitness application, the Strava Metro data is biased towards fitness conscious users and users tend to be male.

123. The caveats of using the Strava Metro data were mainly resolved by completing controlled data collection as part of the study. While this data collection was also done using the Strava application, most of the biases were able to be controlled for. The WCC Officers collecting the data were instructed to walk; this ensured the travel mode was known. The data collectors were of varying levels of fitness and activity. They were new to using the Strava application. While the typical Strava user tended to be male, the WCC Offices collecting the data were a near even split of male and female.

124. The Strava Metro data caveat that couldn't be resolved by collecting data from WCC Officers was knowing the direction of travel. This made it difficult to accurately determine an accurate travel rate for the slopes. This was resolved by using the altered Lorentz function from Campbell et al. (2019) to apply an uphill/downhill adjustment to travel rate on a slope.

125. A caveat with the WCC Walking Network Model is the network data itself. While every endeavour was made to ensure the data is as complete as possible, there will always be gaps. Most of these gaps were found during the testing phase. Testers were asked to examine and run scenarios in areas of the city they were familiar with – such as their home suburb or an area they spent a lot of time in. This allowed the gaps in the network data set to be filled with local, on-the-ground, knowledge. As any additional gaps are found through continued model use, the network dataset will be updated to fill them.

126. Other data gaps will take considerably more time and resources to fill. These gaps are not within the existing datasets forming the Network but include attributes and assets that have not been captured at all (or insufficiently). This includes:

- The location of steps around the city and their height. Some of these assets belong to WCC and others belong to Greater Wellington Regional Council. Both are missing from the network dataset
- Kerb height information is missing from the kerb dataset. This is important information for modelling travel rates and walkable catchments for people with mobility issues
- Width is missing from the pathway data in the network dataset. This information would also be important for modelling walkable catchments for people with reduced mobility
- Terrain surface type is missing from the tracks and pathways data. Terrain surface can negatively impact travel rate (M. J. Campbell 2017) so it would be beneficial to incorporate this information in the travel rate calculations.

127. Collecting this data and preparing it for the model would result in a much larger project. There is currently insufficient resourcing available in Council to take on a piece of work of this scale. Enhancing the Walking Network Model with this additional data will be revisited later when there is sufficient resourcing available.

128. Currently, the WCC Walking Network Model and associated datasets are only accessibly internally, within WCC. It is desired to make this data openly available to the public using WCC's Open Data Portal (Wellington City Council 2022). This will require an upgrade to the Council's internal systems, which is currently in progress. It is hoped that once the upgrades are complete, the data will be made publicly available shortly afterwards.

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