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Incorporating diminishing returns to opportunities in access: Development of an open-source walkability index based on multi-activity accessibility

Josephine Roper
University of New South Wales
j.roper@unsw.edu.au

Matthew Ng
University of New South Wales
matthew.ng@unsw.edu.au

Christopher Pettit
University of New South Wales
c.pettit@unsw.edu.au

Abstract: In this paper, we argue for an explicit decoupling of "walkability" and "walking behavior" and for the advantages of a definition of walkability based on access. This provides impetus for a new approach to constructing and using walkability indices, combining accessibility theory with a goal of comprehensiveness and communicability. Diminishing returns-to-opportunities can be used to map the infinite origin-destination gravity potential space to a finite scale thus creating an easily communicable metric, or metrics. In addition, this method can be applied to any mode and applied to multiple destination types singly or combined. Application of this theoretical approach is demonstrated through the creation of a novel comprehensive open-source transport walking potential index, WalkTHERE. A 0-100 scale is used to represent the percentage of people's total needs potentially accessible by walking. The index is applied to eight Australian and two European cities, and the specific data considerations and parameters chosen are described. Significant disparity is shown in walking access between different destinations within cities, and in walking access between cities. Walking access to recreational opportunities is highest, followed by education and shopping, with very little employment access for most residents. Avenues for expansion and further validation are discussed.

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1 Introduction

The current usage of "walkable streets" was popularized by the work of Jacobs (1961), and the last 20 years have seen many attempts to quantify this concept as a desirable attribute of a location. The well recognized benefits of walkability include wellbeing (Kelly et al., 2018; Schwanen, 2021), fitness (Hoehner et al., 2011), city "vibrancy" and aesthetic appeal (Forsyth & Southworth, 2008), reduced fossil fuel consumption and reduced demand for costly vehicular transport infrastructure (Baobeid et al., 2021).

The term "walkability" is often loosely and broadly used, with varying definitions (Tobin et al., 2022) and has in the last 20 years often replaced less concise but more precise formulations such as "pedestrian accessibility" (Aultman-Hall et al. 1997; Vale 2015), or "built

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environment as a determinant of walking behavior" (Cao et al., 2006; Corti et al., 1996; Forsyth et al., 2008; Frank et al., 2005; Greenwald & Boarnet, 2001; Pikora et al., 2003; Saelens & Handy, 2008). Furthermore, the major interest in walkability by those seeking to improve public health by influencing behavior means walkability is sometimes treated as synonymous with "factors influencing walking behavior."

We argue that conflating "walkability" and "walking behavior" obscures the complex relationships and multiple causal steps between the built environment and walking behavior or health outcomes (Dovey & Pafka, 2020), and limits the utility of walkability as a distinct and robust construct. A typical dictionary definition of "walkable" is "capable of or suitable for being walked" (Merriam-Webster, n.d.), which is in accord with the "-able" root of the word, and different from just "being walked." We argue that this is a useful distinction, as while in practice many walkable places also have high rates of walking behavior, and vice versa, the relationship is not exact.

This paper thus uses an access-based definition of walkability as "the ease of access (which can incorporate quality of walking infrastructure) by walking to desired destinations." This is in line with earlier uses of "pedestrian accessibility" (Aultman-Hall et al., 1997; Vale et al., 2015), and some recent uses of "walkability" (De Vos et al., 2022). In our conceptual model, transport walking behavior occurs following a mode choice decision for each journey, which depends on the relative perceived accessibility available by different modes, amongst other complex factors (Garcia-Sierra et al., 2015; Pot et al., 2021). Accessibility depends on the attractiveness of opportunities reachable by a mode and the generalized cost required to travel to them (both of which may vary for every individual, in a complete treatment of accessibility (Levinson & Wu, 2020)). As well as better explaining walking behavior according to its underlying drivers, this approach also allows consideration of other benefits, such as gains in travel time, opportunity, and financial savings, that may occur due to increased walking accessibility, with or without a change in total walking behavior or health outcomes. (As a thought experiment, consider a city where everyone walks to everything, even long distances. Increased walking access by shortening distances–by densification, or destinations being better clustered together–would result in shorter walks and less total walking behavior, but the residents would save time and effort, and "more walkable" seems the natural way to describe the change.) The accessibility paradigm shift in the broader transport planning literature is understood to be a shift away from designing for mobility to designing for access (Ferreira & Papa, 2020). Walking behavior is technically a measure of mobility, not access, even though it comes with more positive and less negative externalities than are associated with other forms of mobility. Understanding of the differences between these concepts is crucial if walkability indicators are to be used prospectively as a guide to planning, not just retrospectively to identify the areas with most walking out of a limited range of current cities.

Walkability indexes are a useful way to summarize the complexities of walkability in a particular place and potentially guide planning. But the construction of walkability indexes has been limited by a focus on correlation with walking behavior, and underdevelopment of conceptual frameworks. Retrospective indices based on current walking patterns risk reflecting the constraints of existing urban forms rather than the full potential of walkability. For example, a positive correlation can be found between almost any measure of urban density and walking behavior (Dalmat et al., 2021). This does not mean density is a direct driver of walking. The idea that the benefits of density for frequency of walking trips are produced by some combination of local destination access, less parking availability (meaning lower access by car), and better public transport has been discussed for at least 30 years (Handy, 1997, Steiner, 1994). Twenty five years ago Cervero and Kockelman (1997, p. 201) discuss the difficulty of disentangling these issues from density due to data and methodological limitations, thus density formed a primary factor in their classic work on the 3Ds of density, diversity and design. Yet this work remains a major inspiration for walkability indexes–those using a combination of residential density, land-use mix and intersection density or block length—despite the data and methodological improvements available today.

This paper first discusses several avenues for improving multi-activity accessibility measurement, with reference to previous work. It then outlines the application of these ideas to the construction of a walkability index, followed by specific data considerations and parameters for our case study. These include: selection of destination categories, relative weighting of destination categories, assignment of land uses or points of interest to these categories, the accessibility measure used for each category, and the exact cost function or time threshold used within that accessibility measure. We will discuss these before presenting the results of the index for several cities, with commentary. The comparison between different cities illustrates how the index can be used to understand the differences in urban systems and by extension walking in them.

2 Major theoretical considerations for the design of comprehensive multi-activity access metrics

Key elements for consideration in design of an accessibility-based walkability index include: choice of destinations, a meaningful, finite, absolute measurement scale, incorporating distance to destinations rather than a threshold, detailed geographical scale with origins and destinations at building level, and open and reproducible index calculation. No current walkability and accessibility indices have combined these elements (recent reviews: Fonseca et al., 2022; Maghelal & Capp, 2011; Manaugh & El-Geneidy, 2011; Shashank & Schuurman, 2019; Vale et al., 2015). We discuss the importance of each of these elements and how they can be incorporated into accessibility measurement.

2.1 Destination choice and weighting

A positive feature of many walkability indices is the explicit consideration of multiple activities, which has only rarely been applied in more general accessibility measures (Cui & Levinson, 2020; Hou et al., 2019; Klumpenhouwer & Huang, 2021; Zheng et al., 2019). This has generally been done in two ways: by entropy measures of land-use mix, or by lists of destinations considered relevant for walking. The common combination of land-use mix, population density, and intersection density (Cervero & Kockelman, 1997; Frank et al., 2005) measures access to many destinations, but only obliquely via land-use mix. When lists of destinations are used, the destinations chosen are often not well-supported, being based on researchers' assumptions or policy goals (Aultman-Hall et al., 1997; Mavoa et al., 2018; McNeil, 2011; Pearce, 2006), and often focused on leisure, retail and service destinations. In other cases, the destinations were determined by their correlation with currently observed walking behavior (Frank et al., 2021), which we find flawed for reasons given in the introduction. In particular, the failure to consider employment as a destination in these indices limits the full potential of improving walkability in reducing travel distances and energy use because a significant cause for travel is ignored.

Although it may be impossible for every person to live within walking distance of work, our focus is on measuring what exists, not attempting to define what can or should be. The inclusion of employment in an index means small increases (such as created by the addition of affordable housing in city centers) can be measured and highlights the value of specialized employment-accommodation clusters such as university towns.

Therefore, our index includes all types of destinations that people may wish to visit, without preconceptions as to whether it is possible or desirable for them to be visited by a particular mode. Removing assumptions about which destinations can be accessed by which mode also means the same index can be used for any mode, or all modes, by using different networks and impedances. This provides the opportunity to compare access between different modes.

To weight different destination categories, any method that captures a full range of activities, regardless of the current travel mode used, is in line with the goals of this index. Trip frequency has the most widespread data available and captures the amount of travel respondents are willing to undertake towards different goals, but other weightings are possible, such as duration of the day spent at each activity (Cui & Levinson, 2020) or the importance of different "life domains" to quality of life (Zheng et al., 2019). Ideally, data used is local, but trip purpose proportions have proved to be broadly similar in travel surveys between different countries, despite differences in trip rate and trip mileage (Schafer, 2000).

2.2 Finite scale and diminishing returns to opportunities

The most fundamental accessibility measures are open-ended (for example, gravity measures, cumulative opportunities in a threshold, or time to reach some number of opportunities), but walkability measures are often reported as z-scores, standardizing results relative to other cities or other areas in the same city (Frank et al., 2005), and in some cases further normalized to a finite scale (Lam et al., 2022). A similar approach uses quantiles based on ranks (Mayne et al., 2013; Thomas & Zeller, 2021), which also removes the scale of differences. Such indexes differentiate "walkability" between areas, but do not provide any reference point or allow the assessment of multiple changes in walkability occurring simultaneously across or between cities.

We believe the popularity of Walkscore (walkscore.com) may be partly because a finite score from 0 to 100 has greater appeal to the public, policymakers and planners than an open-ended "10,000 jobs reachable" or a relative "3.2 z-score," which only have meaning with reference to comparisons. A finite score can be reached through a normative approach: choosing which destinations provide "enough" walkability, and what distance is "close enough" for a full score. Other destinations are scaled down from there (Mavoa et al., 2018; McNeil, 2011). An example of a normative approach is operationalizing a "15 minute cities" goal by choosing a list of prescribed destinations and checking if they exist within a radius (El-Geneidy & Levinson, 2021).

Another approach to accessibility measurement that produces fixed ceilings is to measure the proportion of total destinations in a city that are reachable from a point (Hou et al., 2019; Klumpenhouwer & Huang, 2021). This has the strength of using current provision of different types of destinations as a guide to residents' needs but does not allow for comparison of absolute destination numbers between cities. We think that a person who can access, say 100,000 jobs has more access than one who can access 10,000, even if they both represent 10% of the jobs in their respective cities (Levinson & Wu, 2020), and this is borne out by on average higher land prices in larger cities (given that land markets are a way to measure the benefits of access to individuals (Roper et al., 2021)). The proportion approach is also not able to measure walkability improvements that occur simultaneously with growth in destination numbers.

Although we reject the simple normative and the proportion-based approaches, we still seek to build a model with a fixed range, but to improve on other normative approaches by better declaring and grounding the required assumptions. Thus, we define our ceiling as the amount of access that fulfils all of a given person's needs. For this index this is approximated to the average person's needs, although noting ongoing developments in modeling accessibility for subgroups or individuals (Klumpenhouwer & Huang, 2021; Levinson & Wu, 2020). More than one destination per category is needed to model this concept, particularly when using broad categories currently available in travel surveys. People prefer different destinations, not just the closest in any defined category, for instrumental, social, cultural and aesthetic reasons and for the sake of variety (Naess, 2012). Rather than choose a fixed number of destinations per category, we think some number will gradually become "enough" for different people's needs.

This concept of diminishing return to opportunities, or declining marginal utility, applying to accessibility, has been discussed (Levinson & Wu, 2020; Pot et al., 2021; Visvizi et al., 2021) but rarely included in models to date. One reason may be the difficulty in determining an appropriate discounting function. Frank's publication describing an early version of Walkscore (Frank et al., 2021) weights each destination in a category based on the best relationship to walking behavior—finding a higher weighting for the furthest destination than the closest. However, in a later published methodology, Walkscore applies a decreasing weight for all categories with multiple destinations (Walkscore, 2011), in line with a theory of diminishing returns. It is not clear how the Index is currently calculated.

Our proposed index uses a negative exponential function. This function asymptotes to 1, providing finite results from potentially infinite destinations, and means only one parameter must be determined for each category: the decay constant λ, rather than deciding the number of destinations per category and how to discount subsequent destinations. Each category continues to reward high destination counts. However, the marginal utility will gradually go to zero—for example, with a decay constant of 0.3, a small town or suburban center with three cultural destinations (e.g., cinema, library, and art gallery) would have a maximum (with 0 travel cost) feature score of 60%. In comparison, a large city with 50 cultural destinations could score essentially 100%. If the utility of these destinations was weighted linearly with a fixed cap, a cap of 50 means the small town has 6% of the cultural destination score of the city—which would probably not accord with resident perceptions of adequacy of cultural destinations in their town. With a lower cap, the large city would not be recognized for its variety and richness of its destinations compared to other towns with 5-10 destinations. The former situation is likely to be produced if accessibility is measured by the total percentage of the city's destinations reachable (Cui & Levinson, 2020), while the latter situation is more likely to be produced by methods measuring a fixed number of destinations (McNeil, 2011; Walkscore, 2011).

The interpretation of a score of 80 is thus that an average person will be able to fulfil 80% of their needs by the mode in question. A score of 100 is difficult and probably undesirable to achieve, since it would require a considerable number of destinations to be located at 0 distance from the home. Introducing a minimum radius of 100% walking propensity within 100m, for example, is a normative (and abled) assumption that is not supported by data—there is a difference, even if small, between a store in the base of someone's building, 50m away, or 100m away.

Employment is modeled like other opportunities: increasing utility with increasing reachable opportunities but gradually diminishing marginal utility. The first is uncontroversial in accessibility, underlying standard measures such as cumulative opportunities, but the second is not. We theorize that the individual utility gained from being able to access large numbers of jobs despite only holding one or a few jobs at a time, is for two reasons. One is the productivity effects of agglomeration translating into higher salaries. The other is precisely because jobs are less substitutable than other opportunities: larger numbers of jobs accessible usually means a broader range of industries, and roles within those industries, are available, increasing the chance someone can find a good fit. This effect tapers off at a point where a wide range of industries and economic sectors are accessible, each with enough jobs that the theoretical individual could change to another role at the same level if they wished. This ceiling is not easy to define; we only argue that there may be a ceiling and some aspect of diminishing marginal returns at work. The relationship between the number of jobs and overall "employment opportunity" is likely very complex and dependent on local economic structure, but we take the negative exponential relationship as a starting point.

2.3 Use of a distance decay function rather than a threshold

What is the effect of distance on walkability? Walkability indexes frequently use a rectangular decay function, counting all destinations, or averaging metrics such as intersection density, evenly within a threshold around a point. Sometimes neighborhood boundaries are used, but defining neighborhoods is a classic example of the modifiable areal unit problem (Flowerdew et al., 2008), and perceived neighborhoods vary widely (Jenks & Dempsey, 2007). There is limited evidence for any particular walking distance threshold being most important, with buffers used in active transport research (e.g., 2400m, 15 minutes) often based on custom or policy goals (Gunn et al., 2017; Prins et al., 2014), or with no justification given (Aultman-Hall et al., 1997; Barr et al., 2019; Forsyth et al., 2008; Greenwald & Boarnet, 2001; Kartschmit et al., 2020; Lam et al., 2022; Liu et al., 2021; Sallis et al., 2016). The many benefits of walkability may have differing relationships with walking distance, but there is no evidence of a sharp change at particular thresholds. In the absence of such evidence, continuous variables should not be dichotomized unless they are highly skewed or there are complex nonlinear relationships with another variable (Streiner, 2002). Although we have outlined the difference between walkability and walking behavior, walking behavior data is the best proxy currently available for establishing the shape of a distance-walkability relationship. The relationship of walking propensity (based on current walking trips) with distance is not linear, but it fits well with an exponential form (Arranz-López et al., 2021; Iacono et al., 2008; Larsen et al., 2010; Millward et al., 2013; Yang & Diez-Roux, 2012) which is still tractable and retains more information than a single threshold.

Thus, the index proposed uses a distance decay function where the ability to walk to a destination varies continuously with distance. To be precise, we use a negative exponential relationship between walking distance and the walkability of each destination.

2.4 Origins and destinations

To analyze access at the pedestrian scale, origins and destinations are ideally located at the level of individual buildings (or even entrances), in contrast to older accessibility and spatial interaction models, which simplify urban space to a series of districts and measure travel times between these districts.

The selection and weighting of destinations in the implementation in this paper were based on the frequency of trips taken from home, so the results are most meaningful relative to the home, but the tool and methodological framework could be used in quite different ways. If studying the walkability of a city center for tourism, the framing question would be what percentage of a tourist's needs they can fulfil by walking, the frequency with which tourists visit different kinds of destinations could be used for weighting, and their potential walking distances to derive a different distance decay factor/s.

2.5 Open and reproducible index methodology

Efficient advances in spatial data science are accelerated by open access—transparent, modifiable and reusable methods. Despite recent interest, open-source approaches to accessibility in general, and pedestrian accessibility in particular, are limited (Liu et al. 2021). With the rise of open data to support more transparent and accountable city planning and design, it is important that digital planning tools and indexes are based on open-source code and data (Hawken et al, 2019).

Walkability indices vary considerably based on the factors included and excluded and algorithms applied and thus should not be treated as an objective measure of truth, but rather carefully examined for applicability in each context, and adapted to the questions being answered (Riggs, 2017; Shashank & Schuurman 2019; Talen & Koschinsky 2013). In recent years, much academic work has used commercialized indexes with proprietary algorithms such as Walkscore, which do not provide a transparent methodology with full details of the algorithms, data inputs and their currency, and thus do not enable critique (Kitchin, 2017), or advances in measurement approaches. A recent review of studies comparing residential property prices to walkability metrics found 20 papers of which 12 used Walkscore—nine as the only metric, three as one of several comparators (Roper et al. 2021).

Walkscore appears to use the same algorithms across all cities and countries—this means there is a lack of customization and contextualization that can be done with respect to local environments. In Chile, WalkScore was found to be of limited utility due to omitting destinations that are of value locally, such as street markets rather than supermarkets, and the high weighting on going out to dine and drink not reflecting travel patterns of Chilean people (Steiniger et al., 2019).

Rather than offering an exact answer of "objective" walkability for every time and place, complex indicators should recognize their own subjectivity and be contextually situated, with transparent provenance and assumptions (Kitchin et al., 2015). Thus, we have developed a flexible and reusable open-source accessibility index, THERE1, which can be adapted to suit other local contexts and particular research questions.

THERE is based on a modularized program structure that makes it easy to trial different parameters—for example the selection of destination categories based on local travel surveys, their relative weighting, the assignment of land uses or points of interest to these categories, networks with different impedances, the parameters governing distance or time decay and the number of destinations per category.

3 Implementation–open-source index for rapid comprehensive access metrics, THERE

The goal of THERE is to answer, on a 0-100 scale, "what percentage of peoples' needs can they access by a particular mode?" where "100" requires an infinite number of destinations and a 0 travel cost to them, but 90 can be achieved with some finite large number of destinations and some small travel cost to them, based on the arguments in sections 2.2 and 2.3 above. This section outlines how such an answer is operationalized in our open-source index.

[1] https://github.com/JosephineRoper/THERE

3.1 Overall index design

The index is based on a gravity measure of accessibility, Equation 1, with terms to be defined through this section. The notation is generally in line with Levinson and Wu (2020).

$$A_{im} = \sum_k W_k * \sum_j U_{jk} * f_k(c_{ijm}) \quad (1)$$

A_{im} is the accessibility from origin i using transport mode m, W_k is the weighting of opportunity/destination type k, U_{jk} is the marginal utility of opportunities at locations j of type k, c_{ijm} is the generalized cost of travel between origin i and destination j by mode m, and $f_k(c_{ijm})$ is the impedance function.

3.2 Selection of destination categories *k*

As discussed above, the categories are recommended to be based on trip purposes measured in household travel surveys, and weighted according to their frequency, but other weightings and choices are possible within the tool.

3.2.1 Assignment of land uses to destination categories

The code provided, for a set of example cities, downloads point of interest data directly from OpenStreetMap (OSM), using the OSMNx Python package (Boeing, 2017), as the most widely available free source internationally. However, there is the option to augment this with other data sources. OSM is not necessarily complete, and completeness varies for different areas (Barron et al., 2014; Briem et al., 2019; Bright et al., 2018). Data on employment locations is imported separately, as the best source for such data is government data such as the number of census respondents reporting a location as their employment destination.

3.3 Opportunity attractiveness of destinations (U_{jk})

The framework accepts any measure to quantify the attractiveness of each destination individually, followed by the application of diminishing value to further destinations as discussed in section 2.2.

WalkTHERE uses a negative exponential curve to represent the decreasing utility of multiple destinations within a category. The marginal utility at each subsequent destination location is:

$$f_k\left(c_{ijm}\right) = e^{-\lambda_k * c_{ijm}} \quad (2)$$

Ideal approaches to determine the parameters of such functions are not established. However, we have estimated one of the parameters for employment. The principle is to fit the model to data that serves as a proxy for our concept of "walkability," as the utility derived from destination accessibility by a particular mode, even though data does not exist on this directly. This is discussed in detail in section 4.3, and the code for this estimation is available as part of the repository.

Although theoretically accepting infinite destinations, for computational efficiency the current index implementation aggregates the nearest 300 points in each category (1200 for employment) and caps the maximum walking distance. This captures well over 99.9% of the possible score with the parameters used for the examples in this paper.

3.4 Cost function and travel cost ($f_k(c_{ijm})$)

The impedance function, representing the diminishing access experienced with increasing travel cost, is a negative exponential function in Equation 3 below.

$$f_k(c_{ijm}) = e^{-\lambda_k * c_{ijm}} \tag{3}$$

Different distance decay parameters can be used for different destination types.

To compute access at a pedestrian scale, using an accurate pedestrian network is essential. Our tool provides two options—direct download from OSM using OSMnx (Boeing, 2017) or import of an alternative network.

The generalized cost of travel is represented by pedestrian network distance in the current model. Other factors can also be incorporated into this framework by uploading or modifying a network with alternative impedances applied to each link. For example, an increased cost could be applied to network segments without sidewalks or with steep gradients or a reduced cost to segments of high visual attractiveness that make walking more pleasurable.

3.5 Origin and destination precision

The network distance tool used, Pandana (Foti & Waddell, 2012), aggregates impedance between network nodes—typically intersections but potentially intermediate nodes if the network is not simplified when represented as a graph. Additional links can be added to the network to join each building perpendicularly with the nearest road, similar to Aultman-Hall et al. (1997). This avoids underestimating walking times with shortest paths that start and finish at intersections.

The size of this underestimation depends on block length between intersections. A 200m long block has an error of 10.5% higher modeled access at the mid-point of the block with a λ of 0.0001. When tested in Sydney, the median absolute difference is 5% because most buildings are not at the mid-block point, and many blocks are shorter than 200m. As building footprint data is often fragmented and incomplete (Roper et al., 2022), and the index takes much longer to run (2-3x) with these additional links, they are not worth adding when results will be visualized across a city or summarized at block locations, but may be worthwhile for property value research. Therefore, code to add these links is available in the project repository but was not used for the examples in this paper.

4 Application of WalkTHERE to ten cities

Here we demonstrate how this index can be applied in practice, to compare walkability in eight Australian and two European cities. The Australian cities are all Australia's state and territory capitals. They have differing histories and built forms, but overall are relatively low density and car-oriented compared to European or Asian cities (Burke & Cui, 2017). Thus we also trialled the index in two European cities, both with a reputation for being walkable (Living Streets, 2017; Shendruk, 2020) but of very different sizes. Edinburgh is similar in population to Canberra, one of the smaller Australian cities, but only a third the area, while the Greater Paris area and population is larger than any Australian city. This range of examples is chosen to illustrate the usefulness of the fixed scale discussed in section 2.2—the results are invariant with the set of cities examined, unlike an index using z-scores. The sub-category results of WalkTHERE in Sydney are shown in detail, with more brief results shown for other cities (full details of all data sources used are available to request).

4.1 Implementation details

4.1.1 Selection and weighting of destination categories

The categories selected are from the Sydney Household Travel Survey (Transport for New South Wales, 2021), weighted according to the number of trips in each category.

4.1.2 Opportunity attractiveness

Data from OSM were used for points of interest. Employment and residential population data were from the relevant government census for each country. Population data (used for population-weighted average results) is available at the meshblock[2] level in Australia, and similar slightly larger areas—the Output Area for Edinburgh and IRIS for Paris.

Table 1. Data sources and attractiveness for destinations

Category	**Opportunity attractiveness O_{jk}**	**Data Source**
Employment	Number of jobs	Census data
Education	1	OSM
Shopping	1	OSM
Errands	1	OSM
Recreation	1	OSM

In the case study, each point of interest has equal attractiveness (1), except for employment opportunities, which are measured in number of jobs (per meshblock, see section 4.1.3 below).

The attractiveness of various destinations within other categories is not uniform, but there is a lack of evidence at present for any particular alternative approach. The floor area of shops or other facilities (Zheng et al., 2019) is also influenced by the price of land. Measures of number of users (Knox, 1978) can accurately predict travel to a facility, but do not necessarily represent "attractiveness" or utility gain, if the quality of facilities may differ but the number who can access them is constrained. (An Australian example would be desirable school catchments.) This highlights the difference between walkability as a predictor of walking behavior, and walkability as a model of utility from access. Capacity constraints are not usually relevant for retail destinations, so a count of customers/day is considered suitable for estimating differential retail attractiveness, if available. Using wages as part of the attractiveness of employment opportunities would be another theoretical improvement. However, business agglomeration is beneficial to productivity (Agarwal et al., 2012), and a common way this productivity is measured is through higher wages. Thus, the number of jobs in an urban center is probably already an indirect measurement of average wages.

4.1.3 Geographical location of employment data

Commonly, accessibility to employment modeling has used areas such as "travel zones" in the US, which range from a few blocks to a suburb in size (Foti & Waddell, 2012). In Australia,

[2] "between 30 and 60 dwellings, with some low dwelling count Mesh Blocks permitted to accommodate other design criteria" (Australian Bureau of Statistics, July 2021-June 2026)

the equivalent smallest scale that place of work census data is released is "destination zone" (DZN) data. Figure 1 below shows the typical scale of Sydney destination zones, although their size is variable. For pedestrian accessibility, this scale is too coarse and representing a DZN as a single point is not accurate. Instead, employment figures for each DZN were assigned to centroids of meshblocks within the DZN having potential employment land uses (all land uses except residential, parkland, water and transport) based on the meshblocks' relative areas. Figure 1 shows the result for the commercial centers of Rockdale, Kogarah, and surrounding residential areas.

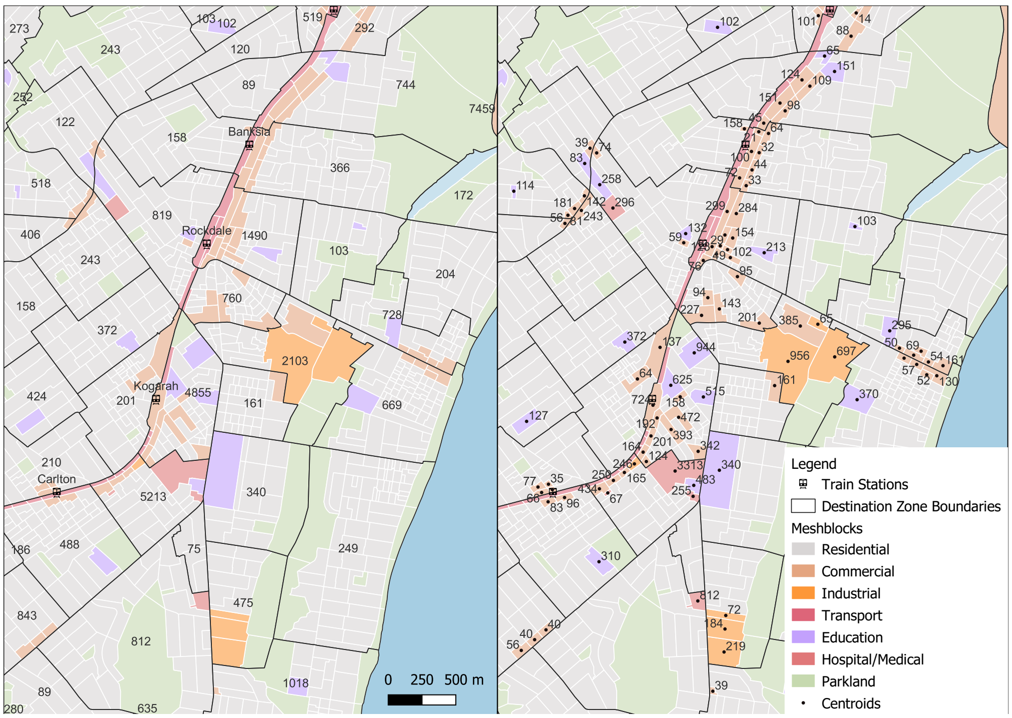

Figure 1. Rockdale area showing numbers of jobs attributed, initially to a Destination Zone, then to the centroids of meshblocks with employment-generating land uses

This method will miss jobs in DZNs composed entirely of residential, parkland, transport and/or water classified meshblocks. However, this represents less than 5% of jobs in Sydney. It will also misallocate jobs that are truly located in primarily residential meshblocks; however, as meshblocks are small units, this will also be only a minor proportion of jobs.

4.1.4 Estimation of parameters for diminishing returns to multiple opportunities

Census data on method of travel to work was used to calibrate the diminishing returns parameter for employment opportunities. The model was based on a conventional spatial interaction model where flows between an origin and destination are proportional to the origin and destination masses and inversely proportional to the distance between them. We use workers living in each meshblock as each origin mass, network distance as impedance, and seek to find the form of the destination mass, that is, the attractiveness of total destinations that can be reached from each meshblock. Thus:

$$T_i = W_i * \lambda_0 * \left(1 - e^{-\lambda_1 A_i}\right) \tag{4}$$

T_i: trips to work with “walking only” mode originating in meshblock *i*

W_i: total workers in meshblock *i* (persons reporting a trip to work by any mode, including work from home, but not “overseas visitors,” “not applicable” or “not stated”)

A_i: sum of distance-weighted jobs accessible from meshblock *i* by walking

λ_0 : scaling factor

λ_1: diminishing returns factor

The decay parameter was estimated at 1.63e-5, after fitting the model using a non-linear least squares method. The fit was also similar in Melbourne, but sparse data for larger job values means these parameters should be treated cautiously and not extrapolated to cities with more significant maximum numbers of jobs available. The scaling parameter λ0 was 0.77; this controls what the function asymptotes to. This means that even with a theoretically infinite number of jobs on their doorstep, 23% of people would still commute by other means than walking. This counter-intuitive result shows that the real relationship between job accessibility and commute mode is more complex than described by this model. As discussed earlier, likelihood of walking to a destination is a function not just of walking access, but negatively related to access by other modes.

In both Sydney and Melbourne, the CBDs have the best public transport access, and good road accessibility (excluding the cost of parking, which is typically bundled into housing costs for CBD residents). Households cannot necessarily locate close enough to walk to 2 or more income-earners’ jobs—but they might locate near the CBD because it has good public transport access to other areas. Consumption activities are also an increasingly important part of urban economies, and in some cases CBDs have a lower job/population ratio compared to middle-tier employment centers (Agarwal et al., 2012). Some residents may live in the inner city for consumption and recreation opportunities, not just proximity to employment.

The difference between walking behavior and walking access potential is critical in linking this commute mode model and our walkability model. For our concept of walking access, we removed the scaling factor, so that the curve approaches one and (effectively) full employment access can be achieved with sufficient jobs available, as shown in Figure 2.

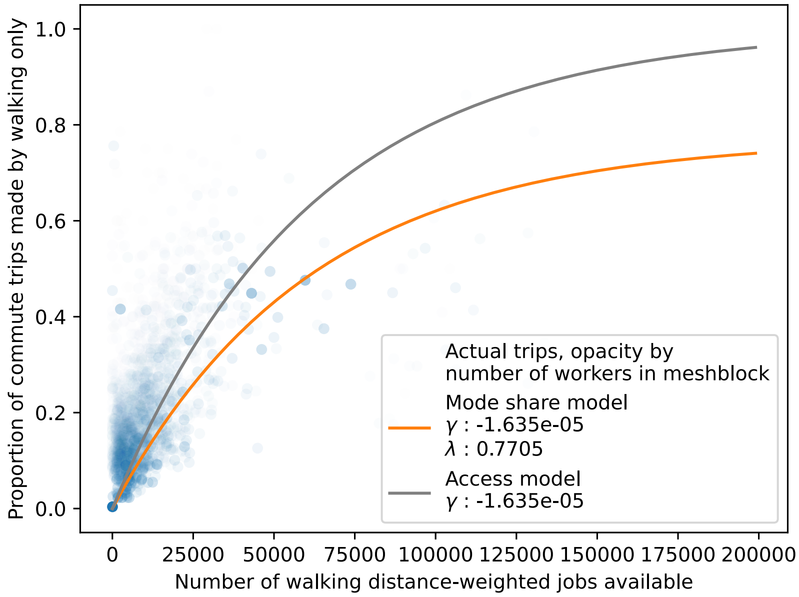

Figure 2. Sydney walkable job access vs walking commute proportion for meshblocks

4.1.5 Travel cost–pedestrian network used

In Australia, the pedestrian network downloaded from OSM (using all road tags except motorway and motorway link) was more complete than the network obtained from Geoscape (the official government source of roads data in Australia), as shown in Figure 3. In other countries, government road data was not examined, but OSM data appears similarly.

Figure 3. Two maps of Chatswood, a commercial center in Sydney, showing the difference in detail between OSM (left) and Geoscape (right) pedestrian network data; additional detail is mostly pedestrian paths through shopping malls, parks, and a train station, which are significant for accurate routing.

The impedance function used a decay constant of 0.001 based on the most common value for walking propensity for various destinations in the literature (Gunn et al., 2017; Iacono et al., 2008; Millward et al., 2013; Yang & Diez-Roux, 2012).

4.2 Results for Sydney including subscores

Results are shown for all subscores in one city, Sydney, in Figure 4. Results for Greater Sydney. The results show face validity in accordance with knowledge of the area. The employment subscore is very low outside a small area around Sydney's eastern CBD. This CBD contains the greatest concentration of jobs and is surrounded by the harbor on three sides, limiting how many people can live within walking distance. High scores for the recreation sub-category are much more evenly spread throughout the city, reflecting good access to amenities such as parks and cafes in most areas of Sydney. Other categories show high scores around smaller activity centers distributed across Sydney, frequently following the locations of major public transport stops. The contribution that Sydney’s partially transit-oriented development pattern makes to walkability is thus reflected despite public transport not being directly included in the index.

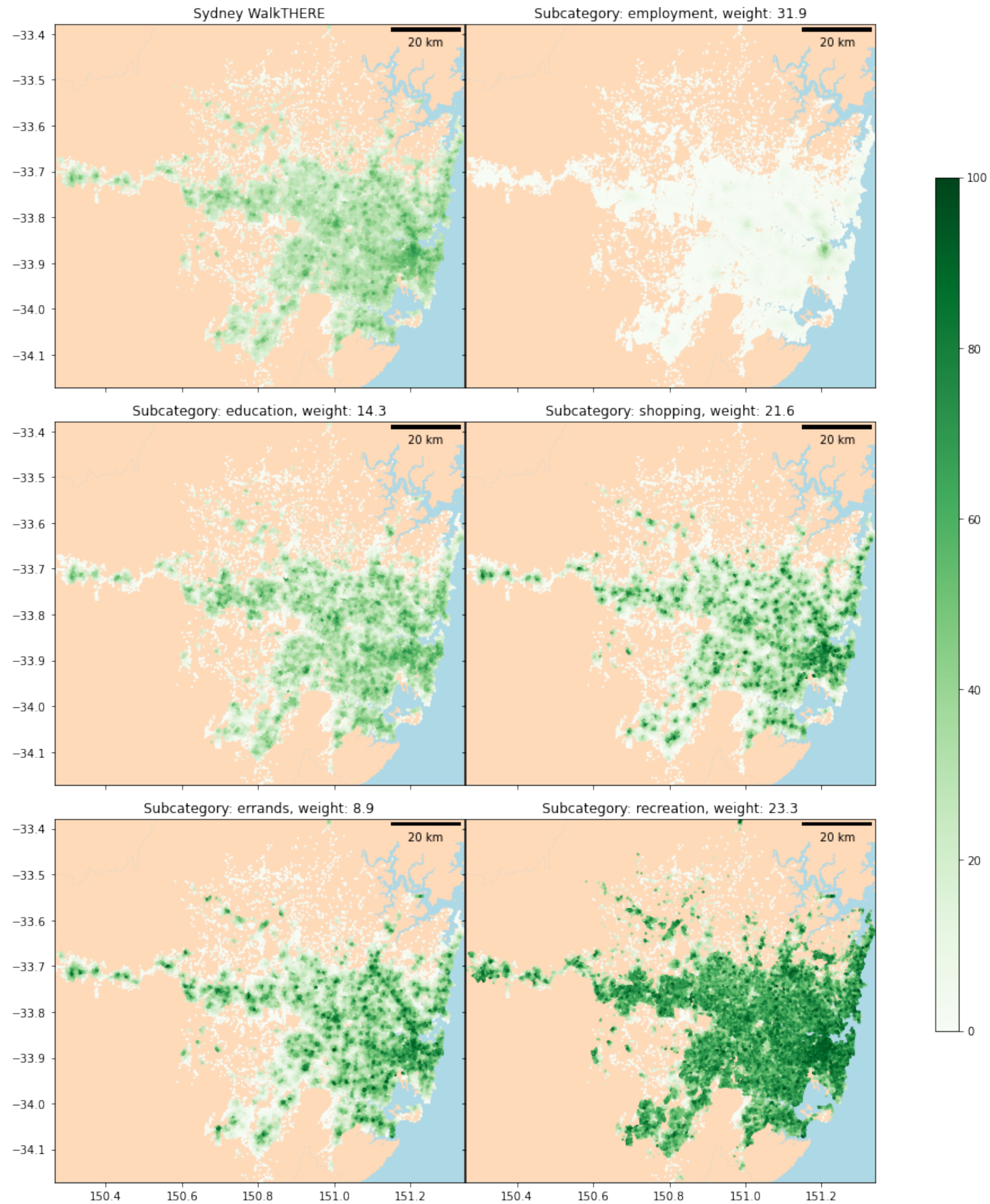

Figure 4. Results for Greater Sydney

4.3 Correlations with walking behavior and existing indexes in Sydney

Although we have made a clear distinction between walkability and walking behavior, a positive relationship between the two is still expected, and provides a starting point for validation of the index design. The index and all sub-scores are positively correlated with the walking commute mode share in Sydney (0.39 overall—ranging from 0.59 for employment subscore down to 0.165 for recreation)—unfortunately similar data is unavailable for other trip purposes in Sydney. The index is negatively correlated (-0.54) with the number of cars per dwelling, in a sub-sample of Sydney meshblocks, though this reduces to -0.31 when controlling for household income in the meshblock.

Comparing WalkTHERE with a popular existing index, the correlation with Walkscore is 0.81 overall in Sydney, similar for shopping, education and personal business sub-scores, 0.55 for recreation and 0.48 for employment. This means the index is likely to perform similarly to Walkscore for research questions. A correlation with the proportion of people who walk to work in Sydney is 0.34 for Walkscore.

An early version of Walkscore (L. D. Frank et al. 2010) uses a comparison of the number of walking trips in the highest vs lowest decile of their walk index (6.45 times greater) to support the construct validity of their index. In our case the same measure is 25.9 times greater walk trips for the commute purpose (corrected for total workers but uncorrected for demographic factors).

4.4 Results for other cities

We present briefer results for the other cities.

Table 2. Average results for comparison cities; areas and populations are those used to generate the results, usually the OSM polygon or a Greater Capital City Statistical Area (Full details can be seen in the repository scripts)

CITY	POPULATION	AREA	POPULATION-WEIGHTED AVERAGE WALKTHERE
PERTH	2,192,000	8,677 km^2	24.5
ADELAIDE	1,402,000	1,692 km^2	27.3
CANBERRA	454,000	740 km^2	28.5
HOBART	251,000	1,024 km^2	24.1
DARWIN	149,000	162 km^2	27.6
BRISBANE	2,569,000	1,378 km^2	31.0
SYDNEY	5,260,000	4,316 km^2	32.3
MELBOURNE	4,976,000	8,912 km^2	31.4
EDINBURGH	477,000	273 km^2	47.2
PARIS (GREATER)	11,840,307	12,065 km^2	45.2

The results are in line with expectations, with the oldest Australian cities tending to have the highest mean scores. Lowest performers are younger cities designed around the road network and containing many disconnected, curvilinear suburbs. The results for smaller cities are also lower, partly because of the high ceiling for employment access. This is a strength of the index—it is able to provide meaningful comparisons between vastly different cities. The fact it is more expensive and desirable to live in the center of Paris vs Melbourne vs Hobart is primarily due to differing job markets. All three cities have high-scoring areas where every other sub-category is close to the maximum possible, indicating other amenities sufficient to fulfil nearly all of residents' needs are within walking distance.

The population-weighted results in Figure 6 show how the presence of areas of the CBD with a score over 70 in Sydney and Melbourne does not necessarily contribute much to the experience of very high walkability around homes across the population because of the low population in these CBD areas. For many, the separation between home—often in low-density suburbs—and work—limits overall walkability. Meanwhile, the Edinburgh and Paris results show that with a different urban form, it is possible to have a much greater fraction of the population dwelling over 70.

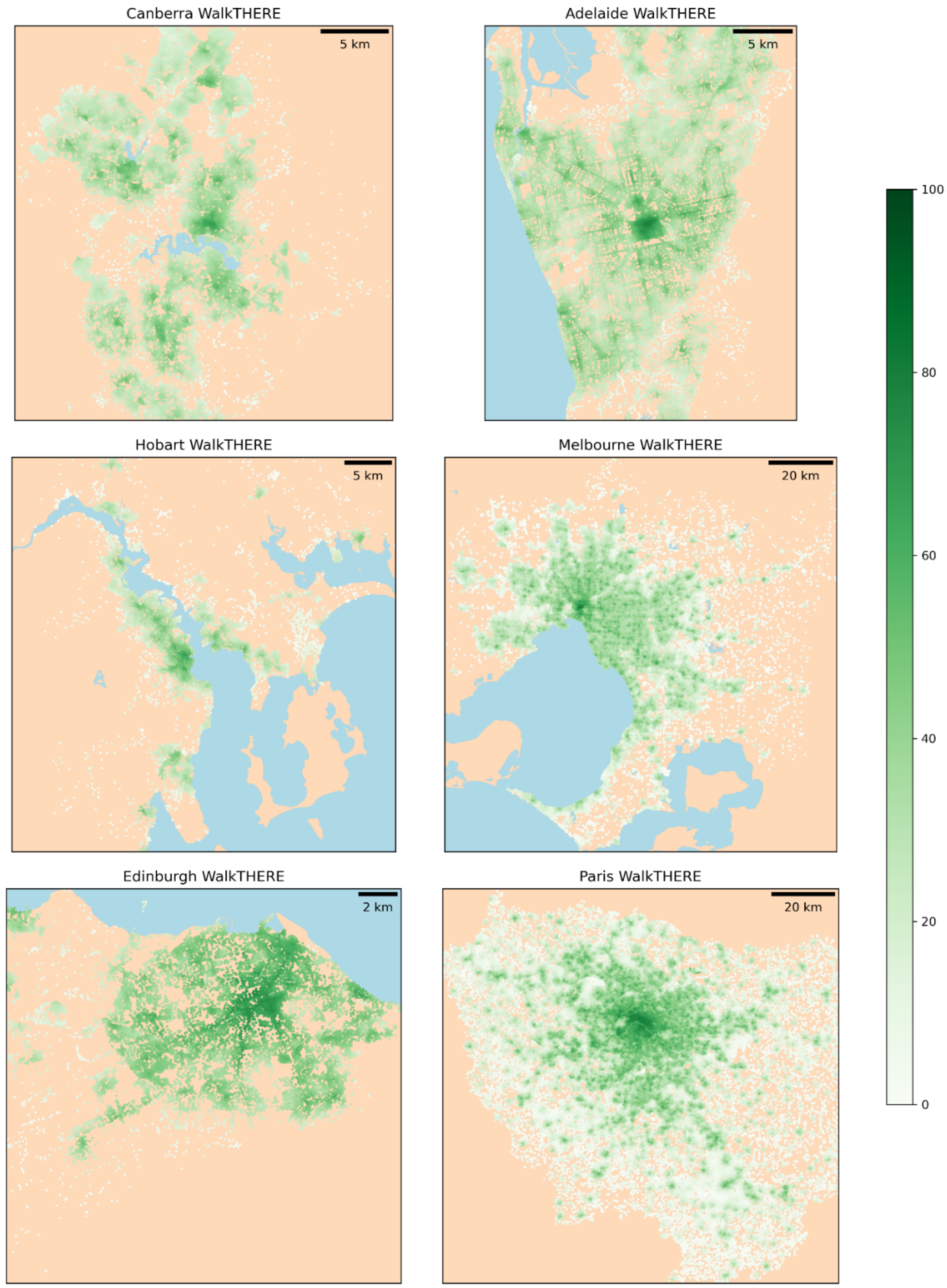

Figure 5. Results from other cities for overall walking index

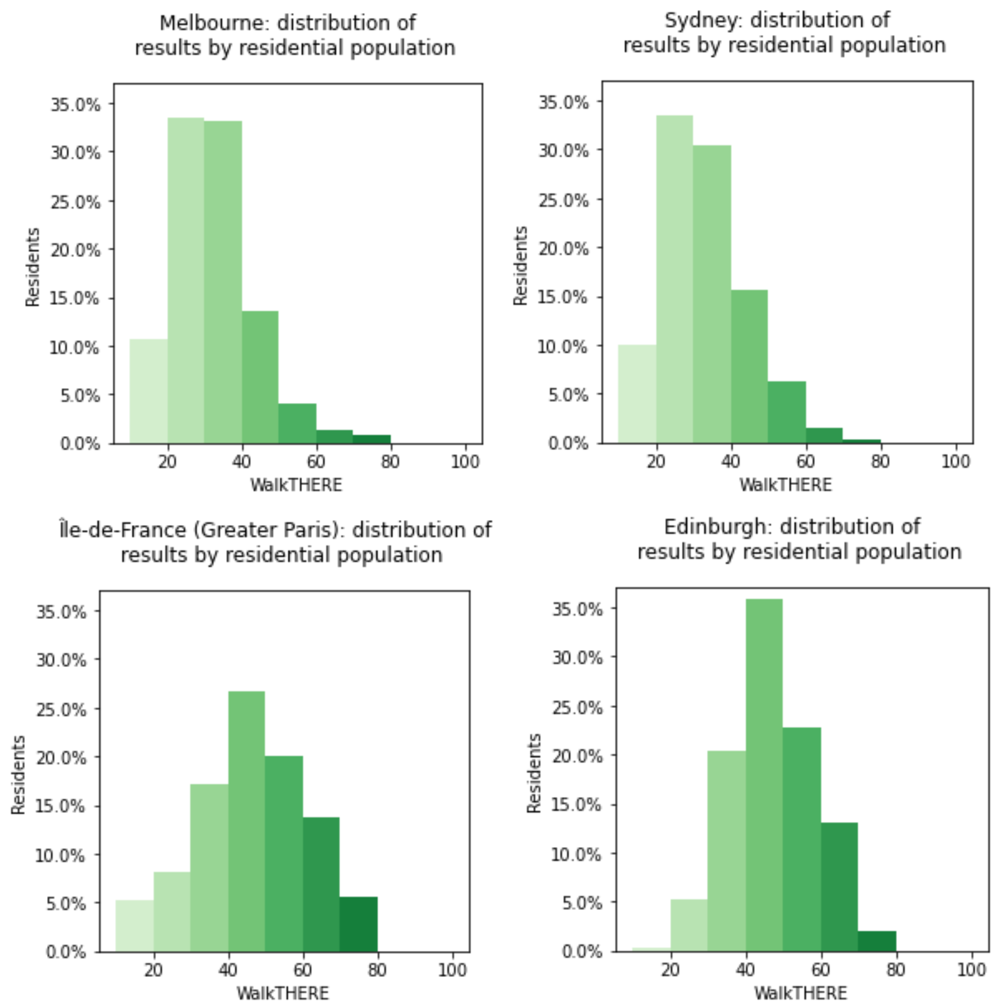

Figure 6. Population weighted results for Melbourne, Sydney, Edinburgh and Paris

5 Discussion

We have argued for the utility of taking an accessibility approach to walkability. We have described a detailed model for doing so and demonstrated its application across a range of cities. The results show that the index can be easily applied to a range of cities and that the results for these cities have face validity.

Our results shows that WalkTHERE also meets (and exceeds) measures of "construct validity" used for previous walkability indexes. The dominant approach to overall validation for walkability indices has been to measure walking behavior. However, we argue, and Dalmat et al. (2021) show, that a positive relationship with walking behavior is true of many measures, including simple measures of urban density. We appreciate this attempt to bring rigor to validation by comparing multiple measures, but this is validating these measures for a specific purpose—as a predictor of walking behavior. Separating walkability from walking behavior means an index cannot and should not be constructed simply by finding the best relationship with walking behavior. Insofar as we define walkability in terms of opportunity to walk places (to meet an individual's needs), whether or not it is taken up, WalkTHERE could be further validated against stated preference or perception data, or against revealed preference data that is additive, such as property prices. The theory is that using hedonic price modeling, people will pay more to live in a place with excellent walkability and excellent public transport accessibility than in one with mediocre walkability and excellent public transport accessibility, allowing interpretation of perceived walkability in a way that may not be visible in walking behavior data. Additional forms of validation would come from studying the utility of this index for city planners, developers and residents.

5.1 Limitations

Destinations that are polygonal in the data sources were reduced to their centroids before distance measurement. This is not entirely accurate for large area destinations such as parks or shopping centers—all possible entrance points would better represent access. Destination attractiveness is also limited by OSM data not necessarily being complete.

The lack of consideration of streetscape in the current results means results are not accurate for people with different mobility needs, although in Australia, the difference is smaller than in many other countries as cities generally have good coverage of footpaths and curb cuts. With comprehensive data on streetscape elements available, the index could be run with different networks representing the impedance for people with different needs.

Data on employment locations—numbers of jobs available at a sufficiently fine detail to be meaningful for walkability—is difficult to find in many countries. Data such as jobs per suburb is insufficient, as they are likely neither evenly spread nor concentrated in the suburb's center. For the examples here, we used a method of imputation from larger zones. Other localities might be able to develop other imputation methods, such as estimates based on open data on business locations and building sizes.

5.2 Future research

There are four most promising avenues for future research—consideration of trip chaining effects, application to other modes, improving the model of generalized cost of travel for walking, and approaches to validation and parameter selection that do not rely on current walking behavior.

An important addition is the consideration of destination clustering and trip chaining effects. Many walkability indexes include access to public transport stops, which we did not. A public transport trip may contribute to overall walking behavior, and there is a difference between a suburb where people drive to the station and one where people walk to the station, but both trips occurring depends on public transport accessibility, not walking accessibility. However, considering stations becomes important when clustering of destinations is added to the index. In Sydney, a frequent land-use pattern is activity centers clustered around public transport. This results in improved public transport access to those local destinations, but also provides value through potential trip chaining for those living near the activity center. Thus, rather than simply assigning some value to public transport stops, we plan to develop a combined walking and public transport network model and incorporate trip chaining to capture how more or less convenient public transport stop locations provide accessibility benefits.

Although the index can be applied quickly to other modes if using a simple impedance such as time or distance, calculating a more accurate generalized cost of travel is more complex, including travel time that varies throughout the day, variable perceptions of travel time, access to vehicles, monetary costs, safety and perceptions of safety. Full cost accessibility—considering external costs such as emissions and risk to others (Cui & Levinson, 2018) is a further elaboration with different applications, such as fairly pricing transport options to minimize societal costs, whereas our index is focused on individual utility.

There are opportunities to improve the calculation of the generalized cost of walking, for example incorporating evidence that people dislike waiting at traffic lights more than walking, and testing the effects of many factors of pleasantness and walking experience that have been suggested as significant in previous literature (Day et al., 2006; Ewing & Handy, 2009; Quercia et al., 2014). The ability to modify network costs for different subgroups also offers opportunities to test the use of the index, such as for optimizing cities for an ageing population.

The implementation shown here uses walking behavior data to calibrate one parameter (diminishing returns to job opportunities), but as discussed in the introduction and section 4.1.4 this is a simplified model based on currently available data, and we plan to explore alternative data sources that can shed light on this issue of diminishing returns calibration. In particular, we plan to gather data on perceived walking access (Pot et al., 2021) to improve the model, potentially using participatory mapping platforms for broader and simpler data collection than in previous approaches to perceived walkability (Roper et al., 2022).

Future research will also test the comparative performance of WalkTHERE in property value modeling, to see if performance improves over that previously found with Walkscore and whether exploration of model parameters can provide clues to understanding apparent inconsistencies or idiosyncrasies produced by the Walkscore property pricing correlation (Roper et al., 2021).

6 Conclusion

While the walkability concept has widespread appeal, problems identified with previous walkability indices include the use of indirect access proxies, destination choice based on assumptions about a limited range of destinations being "walkable," and reliance on behavior outcomes to validate indices. Some of the most sophisticated and commonly used metrics such as Walkscore are not open-source; thus, researchers and planners cannot assess the assumptions made or their relevance to their walkability measurement needs. Much walkability research focuses on health benefits from increases in walking behavior, but walkability has broader benefits than this, which an access approach can help to illuminate.

We have demonstrated the construction and deployment of a novel comprehensive accessibility index that addresses some limitations of previous work. It can rapidly display results from a wide range of cities if employment data is available, although it can also be modified to remove this category.

Despite the argument that quantification and production of indicators are overdone in urban research (Kent et al., 2022), we still think there is a gap in producing metrics that have intuitive meaning for users. Although El-Geneidy and Levinson (2021) argue for straightforward measures such as cumulative opportunities, and our index is more complex to understand, we show that it is motivated, and can be explained, by a simple question: what percentage of an average resident's needs can be accessed by a particular mode.

We answer this question in a robust way using several key features: using a comprehensive set of destinations with weighting from travel surveys, using a gravity model rather than choosing thresholds, and modeling the effect of an open-ended number of potential destinations per category, in a way that respects econometric arguments for decreasing marginal utility of opportunities. The result being the creation of a multi-activity accessibility index that can be used to produce context specific outputs, including modeling effects of proposed improvements.

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