Data-Needs-Report

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## Abstract

Active travel is a key element to achieve robust and healthy urban transportation polycultures. As analysis of transportation needs in cities shifts from a focus on mobility to accessibility, the need to assess accessibility by cycling and walking has become increasingly pressing. The distinguishing features of these modes –lower speeds, shorter trips, potentially different purposes compared to motorized trips– means that the data inputs required for accessibility analysis are not necessarily the same as those used for the study of accessibility for motorized travel. The objective of this review is to assess the sources of data and data needs to implement active accessibility analysis. Walking-specific and cycling-specific geographic accessibility measures and data applied within recently published literature are reviewed. Walking and cycling accessibility measures are compared in terms of the types of metrics, the origins and destinations considered, geographic scales, and travel time or distance calculations. In comparing approaches for walking versus cycling, this report also highlights possible considerations, challenges, and questions that emerge when considering the future of active travel accessibility-based analysis. The discussion in this review is centered on the Canadian context but the lessons may be more broadly applicable to other national contexts.

## Introduction

For decades, transportation planning has been focused on providing mobility for the private car. This is a development model that was first introduced in North America as a solution to problems caused by rapid urbanization and was later copied elsewhere (Angotti 1996; Brown, Morris, and Taylor 2009a). It is now clear that mobility centered on the private car is inefficient, inequitable, and unsustainable that require immediate attention. This includes environmental issues (i.e., climate change; (Chapman 2007)), as well as numerous other social (Boschmann and Kwan 2008; Lucas 2012, 2019), health (Khreis et al. 2016; Milne 2012) and equity concerns (Bocarejo S and Oviedo H 2012; Martens, Golub, and Robinson 2012; Pereira, Schwanen, and Banister 2017). In order to reduction of car use, the transportation agenda has aimed to focus on creation of mobility polycultures that offer a border menu of transportation alternatives (Lavery, Páez, and Kanaroglou 2013; Millera 2011). Polycultures are resilient and adaptable systems with numerous mobility options, including mobility substitutes such as information technologies and this is more complex than a monoculture in that it requires not only a broader range of mobility technologies, but also a much higher level of coordination among modes and travelers. So, active travel is a key component of efforts in urban areas as they try to achieve more robust and healthy urban transportation polycultures (@ Millera 2011; Lavery, Páez, and Kanaroglou 2013; Lira and Paez 2021).

Cycling and walking are effective modes for short- and mid-range travel in urban areas that have, over a period of decades, grown to accommodate travel by automobile (Brown, Morris, and Taylor 2009b; Wiersma et al. 2020) while treating other modes almost as afterthoughts (Brezina, Leth, and Lemmerer 2020; Koglin 2020; Ruffino and Jarre 2021).On the one hand, there are concerns about the externalities of the current (car-centeric) transportation system; on the other hand, there is a growing understanding and awareness of the numerous co-benefits of active mobility in terms of health, efficiency, and social inclusion (Banister 2005; Gärling, Ettema, and Friman 2014; Gössling et al. 2019; Mueller et al. 2015). Along with a focus on motorized travel, the focus of transportation planning has been to plan for mobility mainly by car. Transportation and land use systems have been designed to produce mobility, and this is reflected in the use of measures of efficiency that ignore the reason for most travel, which is to reach destinations (S. L. Handy and Niemeier 1997).

The idea of producing mobility seems intuitive when planning for inexpensive motorized travel, in an era when automobile users have been, as a matter of policy, shielded from paying –and even becoming aware– of the full cost of their travel (Taylor 2006). In recognition of the contradiction of trying to generate mobility while also hoping to reduce the ill effects of mobility, an argument in the transportation literature for decades has been to shift from mobility-based to accessibility-based planning (S. L. Handy and Niemeier 1997; Social Exclusion Unit 2003). Transportation accessibility is commonly defined as the potential of transportation-land use systems to generate access to opportunities (Páez, Scott, and Morency 2012) and conceptually strikes at the heart of wasteful mobility-based planning by focusing on the ability to reach destinations. Despite mixed evidence regarding the adoption of accessibility in planning practice (Boisjoly and El-Geneidy 2017; Proffitt et al. 2019) there are reasons to believe that the future belongs to accessibility-based planning (S. Handy 2020).

The relevance of accessibility-based planning is even more evident when active modes are considered: who would rather make long trips if equivalent destinations could be reached with shorter trips? Not only can pedestrians and cyclists not be shielded from the cost of travel, the effort of reaching destinations is inherently visceral (Hsu and Tsai 2014; Iseki and Tingstrom 2014; Páez et al. 2020). As interest in active travel-based accessibility (ATB accessibility) grows globally (Arranz-López et al. 2019; Li, Huang, and Axhausen 2020; Ortega et al. 2021; Rosas-Satizábal, Guzman, and Oviedo 2020), transportation scholars have built on decades-worth of accessibility research that mainly focused on motorized travel. In principle, accessibility analysis is sufficiently general to be applicable for ATB accessibility analysis. In practice, it is important to recognize the differences between motorized and active travel, and how they can impact their implementation with a focus on active travel (Iacono, Krizek, and El-Geneidy 2010). Active modes of transportation absorbed the interest of researchers because they have significant implications and combines unrivalled advantages such as environment, health, and social inclusion (Pucher et al. 2010; Rojas-Rueda et al. 2011, 2012; Otero, Nieuwenhuijsen, and Rojas-Rueda 2018; Koszowski et al. 2019; Tinessa et al. 2021). They have been linked to a variety of health benefits. For example, they improve longevity (Hakim et al. 1998), cognitive function (Weuve et al. 2004), quality of life (Strawbridge et al. 1996; Leveille et al. 1999), and are perceived as cleaner and more efficient sustainable modes of transportation (Bhopal and Unwin 1995). They also become an excellent alternative for decarbonizing mobility, lowering transportation costs for families, promoting gender equality, building resilient structures, and contributing to the aesthetic value of the environment (Koszowski et al. 2019). They also improve accessibility for those who do not have other modes of transportation and aid in the development of local and regional economies. However, compared to motorized travel, active travel is slower, occurs on smaller scales, has less safety due to their higher risk of being severely injured in collisions than motorized vehicle drivers, is used to reach potentially different destinations, and involves costs, such as physical effort, that are typically ignored in motorized travel analysis (Ng, Debnath, and Heesch 2017; Akgün et al. 2018; Pokorny, Pritchard, and Pitera 2018; Oehl, Brandenburg, and Huemer 2019; Useche et al. 2019).

The objective of the present study is to investigate ATB accessibility with a focus on data sources and needs, using Canada as case study. The research is prompted by a recent Canadian project that has been tasked with developing data-driven standards for the analysis of transportation equity. The need to propose methods that can be used consistently across regions requires a sound understanding of how analysis and outputs can be conditioned by the data inputs. it is important to acknowledge that other reviews of ATB accessibility measures exist (Geurs and Van Wee 2004; Iacono, Krizek, and El-Geneidy 2010; Maghelal and Capp 2011; Talen and Koschinsky 2013; D. S. Vale, Saraiva, and Pereira 2016). The contribution of this paper is to fill a gap in the literature by focusing on the data required by various measures of ATB accessibility and comparing measures that can be implemented consistently in different contexts, as well as data needs for consistent implementation of the rest.

The reminder of this paper is organized as follows. Section 2 presents a review of methods. Section 3 presents a categorization of the required data according to each of the accessibility measurements. Section 4 provides Important considerations and possible challenges for calculating accessibility by active mode; discussions and conclusions are provided in Section 5.

## Background

Transportation planning has emerged as a distinct field centered primarily on mobility, defined as the ease of movement. Mobility indicators such as travel speed and travel time were proposed in this context, with a focus on motorized transportation (Banister 2008). The concept of accessibility has long been adopted in both spatial and transportation research to assess the quality and extent of the relationships between spatial development of a certain area and the transportation system serving it. The seminal work of Hansen (1959) defined accessibility as “the potential of opportunities for interaction”, measuring the number and variety of opportunities which can be obtained from a specific location by means of the transportation system.As a result of Hansen’s work, researchers began to emphasize the importance of including accessibility as a performance indicator in land use and transportation plans as an alternative to mobility-based transportation planning (Koenig 1980; Morris, Dumble, and Wigan 1979; Wachs and Kumagai 1973). Furthermore, the researchers argued that improved access reflects the network’s economic and social benefits, specifically in terms of land value and quality of life (Koenig 1980; Wachs and Kumagai 1973). Recently, accessibility has been promoted as a critical component of land use and transportation planning, specifically in terms of social equity, economic development, and environmental impacts (Banister 2008; S. L. Handy 2002; Lucas 2012; Preston and Rajé 2007). For example, in 2004, Geurs and van Wee deconstructed the concept of accessibility into four elements: (i) Land use describes the quality, quantity, and spatial distribution of opportunities as destination places, such as schools, jobs, hospitals, and recreational facilities, as well as demand for opportunities at origin places; (ii) Transportation refers to the transportation system represented by the disutility for a person to travel from an origin to a destination using a specific mode of transportation; (iii) time, which accounts for the time constraints in terms of the availability of opportunities throughout the day and the time available for people to take advantage of such opportunities; and iv) Individual, which indicates specific (groups of) people’s capabilities (determined by income, education level, travel mode availability, etc.) and needs (determined by age, household situation, etc.).

Mobility-based approaches emphasize travel time reduction, whereas accessibility planning aims to provide all individuals with a reasonable travel time to a variety of destinations. As a result, accessibility planning prioritizes active and public transportation and incorporates land use policies that shorten distances between activities(@ Banister 2008).Accessibility refers to the ease of access to different destinations which are valuable and can be reached. In order to calculate accessibility, the implementation of access measures varies depending on the research need, mode of transport, data need, activities, and land use pattern, as well as the costs of travel over the transport infrastructure that connects it. So, the emphasis on different elements of accessibility has resulted in multiple measurement methods and indicators (for example, Geurs and Van Wee 2004; Kelobonye et al. 2019; Lee et al. 2010; Neutens 2015; Paez et al. 2010; Vandenbulcke, Steenberghen, and Thomas 2009), including proximity, cumulative, gravity, utility-based, and space-time prism models as the dominant approaches. However, there are disagreements about how to evaluate this concept (Castiglione et al. 2006; Fan, Guthrie, and Levinson 2012; Wang and Chen 2015).

In general, accessibility can be measured at the individual-based or locational level (place-based) (Miller 2005).In general, accessibility can be measured at the locational level (place-based) or the individual (person-based). Indeed, place-based metrics are concerned with the land use and transportation components, and focus on the physical separation of key locations, say an origin and potential destinations. This kind of accessibility refers to the degree to which people can reach and use services, amenities, and opportunities located in a specific geographic location, such as a neighborhood, city, or region.On the other hand, individual-based metrics take into account some representation of the space-time behavior of individuals and refers to the degree to which an individual person can reach and use services, amenities, and opportunities based on their personal characteristics, such as age, gender, income, mobility, and health status. Individual-based accessibility considers the unique needs and preferences of individuals, including their ability to access different types of transportation, travel routes, and modes of transportation. Individuals-based accessibility is sometimes included in location-based studies by stratifying the population by age group or socioeconomic characteristics, as well as by segmenting destinations (Harris 2001; D. de S. Vale 2009; Paez et al. 2010; Fan, Guthrie, and Levinson 2012; Legrain, Buliung, and El-Geneidy 2015, 2016).These two approaches are related, and individual-based measures can in fact be seen as a special case of placed-based measures, where the impedance function and cost are a constant by origin.

To write a formula for placed-based accessibility for active transportation modes, we can modify the formula, by taking into account factors that are specific to active transportation. Here is one possible formula:

D represents distance to the destinations that are of interest. W\_D and W\_T are weights that reflect the relative importance of each variable in determining accessibility.and T represents the travel time required to reach the destination(s) using active modes of transportation. (1 - w\_D) and (1 - w\_T) represent the proportion of destinations that can be reached from the origin location and the travel time required to reach them, respectively.E represents the energy expenditure associated with active transportation, which is a function of the distance traveled, the speed, and the incline of the terrain.w\_E represents the potential energy expenditure associated with active transportation, with higher values indicating greater accessibility.S represents the safety of the walking or cycling environment, which can be influenced by factors such as traffic volume, speed limits, road design, and presence of pedestrian or bicycle infrastructure.w\_S represents the perceived or actual safety of the walking or cycling environment, with higher values indicating greater accessibility.Other factors that may influence accessibility for active modes include the quality and attractiveness of the pedestrian or cycling infrastructure, the availability of amenities and services along the way, and the social and cultural factors that affect the willingness and ability of people to walk or cycle. These factors can be included in the formula as additional variables or weights, depending on the specific context and research question.

Calculating place-based accessibility in active mode (e.g. walking, cycling) can be challenging due to a variety of factors. Some of the main restrictions for calculating place-based accessibility in active mode include:Physical barriers, such as hills, rivers, and other natural obstacles, can make it difficult for people to reach specific destinations. These impediments can lengthen and complicate a person’s journey, making it less accessible; Concerns about safety, people who walk or cycle are concerned about their safety, and certain areas may be deemed unsafe due to high traffic volumes, crime rates, or poor infrastructure. People’s willingness to travel to certain destinations may be limited by safety concerns, reducing accessibility; Weather conditions can also impact active mode accessibility. Extreme temperatures, precipitation, and other weather events can make walking or cycling difficult or dangerous, limiting accessibility; The availability and quality of infrastructure such as sidewalks, bike lanes, and pedestrian crossings can have a significant impact on active mode accessibility. People may be less likely to choose active modes of transportation in areas with poor infrastructure, reducing accessibility; Individual abilities and limitations, such as physical disabilities, can also have an impact on people’s ability to travel in active modes. People with disabilities may find it difficult to navigate the urban landscape due to a lack of accessibility in the built environment.

We can modify the formula for placed-based accessibility to include individual-specific factors in order to write a formula for individual-based accessibility for active modes. Here is one example of a formula.

The function f represents the relationship between these variables and can be represented mathematically in a variety of ways depending on the context and assumptions. D, T, E, and S are the same as in the previous placed-based accessibility formula.P represents the individual’s personal characteristics, such as age, gender, physical ability, and trip purpose.w\_P represents the individual’s personal characteristics that influence their ability and willingness to walk or cycle, such as age, gender, physical ability, and trip purpose.Other factors that may influence individual-based accessibility for active modes include the individual’s preferences and attitudes towards active transportation, their social and cultural context, and the availability and quality of supportive policies and programs. These factors can be included in the formula as additional variables or weights, depending on the specific context and research question.

Individual-based accessibility in active mode (e.g., walking, cycling) can also be difficult to calculate due to a variety of factors. Some of the major constraints for calculating individual-based accessibility in active mode are as follows:

1.Individual preferences for modes of transportation can have a significant impact on accessibility. Some people prefer to walk or ride their bikes, while others prefer to take public transportation or drive. Factors such as distance, time, safety, and comfort can all have an impact on personal preferences.

2.Physical ability: Similar to place-based accessibility, personal physical ability can greatly impact individual-based accessibility in active mode. People with disabilities or health issues may find it difficult or impossible to travel by foot or bike, reducing their accessibility.

3.Time constraints: Work schedules, childcare responsibilities, and other obligations can limit people’s ability to travel actively. In order to save time, people may choose faster modes of transportation such as driving or taking public transportation, reducing accessibility in active modes. While individual-based accessibility is measured, it should be recognized that every individual has a different opportunity set available (Miller 1991). Effectively, the available time threshold (t) varies for each person as a function of individual constraints, such as time of day, purpose, and so on. Constraints arise for a number of reasons. Time geography acknowledges that spatial and temporal characteristics limit an individual’s choice of activities. A person can only be in one place and do one thing at a time (Chi et al. 2013; Pred 1977; Miller 1991; Miller and Bridwell 2009).These restrictions are classified into three types.The first section is capability constraints, which are biological and physical limitations that prevent people from participating in certain activities; The second section discusses authority constraints that restrict access to specific locations and the third section discusses coupling constraints, which are common in activities that require two or more people to be in the same place at the same time.In addition to these three categories, it should be noted that constraints vary depending on the time of day (H. Wu and Levinson 2020).Time constraints can be visualized using a time-space diagram, the size of which is determined by both the amount of time available and the performance of the transportation system (Ilägcrstrand 1970).The space-time prism accounts for an individual’s activity schedule and can be used to measure access to multiple activities and activity participation time using simple behavioral rules (Miller 1991). Accessibility is measured by the total number of opportunities available within the space-time prism encompassing all possible paths under the time constraint (Tong, Zhou, and Miller 2015).So, while opportunities may be spatially accessible, the amount of time available in a day for people to reach and engage in these activities is limited. This line of thought leads to the constraints-based or people-based accessibility measure(Y.-H. Wu and Miller 2001).

1. Weather conditions, like place-based accessibility, can have an impact on individual-based accessibility in active mode. In extreme weather, people may be less likely to walk or cycle, reducing accessibility.

5.Infrastructure: The quality and availability of infrastructure such as sidewalks, bike lanes, and pedestrian crossings can greatly impact individual-based accessibility in active mode. People may be less likely to choose active modes of transportation in areas with poor infrastructure, reducing accessibility.

Accessibility measures in active modes include activity-based measures, distance-based, topological or infrastructure-based measures, utility-based measures, as well as, walkability, and bikeability. Activity-based measures (includes gravity-based and cumulative opportunities measures) are based on the gravity model and weight opportunities according to a travel impedance function and the accessibility of a place is assessed as the combined effect of the size of opportunities and the cost of traveling to them. Distance-based measures analyze the closest facilities and include: 1) distance to the closest opportunity, 2) the number of opportunities within a defined distance or time, 3) the mean distance to all opportunities, and 4) the mean distance to a defined number of closest opportunities. Infrastructur -based measures are based exclusively on features of the street and transportation network and are insensitive to the location of activities in space. utility-based measures (also designated benefit measures) are developed from microeconomic random utility theory and describe accessibility as the result of a (rational) choice from a set of destination transportation alternatives (Kwan 1998; Halden et al. 2000; Geurs and Ritsema van Eck 2001; Apparicio et al. 2008). Walkability and bikeability measure the number of people, households or jobs distributed over a unit of area or measures how many types—offices, housing, retail, entertainment, services, and so on—are located in a given area (L. Frank, Engelke, and Schmid 2003; Leslie et al. 2007). Indeed, using accurate accessibility measures for walking or cycling trips can assist transport planners in making more rational decisions in infrastructure provision for non-motorized transportation (Iacono, Krizek, and El-Geneidy 2010; Devkota, Dudycha, and Andrey 2012).

Moreover, calculating ATB accessibility in both approaches requires multiple data sets relating to travel behavior and land use. Unfortunately, this has suffered from a lack of appropriate data(Iacono, Krizek, and El-Geneidy 2010). In particular, little information is available on the geography of walking and cycling behavior such as travel episode origins and destinations, routes, and lengths (durations and distances). So, in most cases, required data is obtained from local/national questionnaires and local maps (Iacono, Krizek, and El-Geneidy 2010; Levine 2010; Devkota, Dudycha, and Andrey 2012; Yang and Diez-Roux 2012; Millward, Spinney, and Scott 2013) . In addition, available data are extremely location specific or cover a small geographic area and are not adequately covered in most large-scale survey instruments, such as national transportation survey (Ulmer and Hoel 2003; Achuthan, Titheridge, and Mackett 2007).

## Methods for ATB accessibility analysis

Research about walking and cycling tend to categorize these modes into two different parts of literature (The first is about health and leisure and the second is about transport and land-use), and both have their own viewpoints, data, methods, and policy orientations (Pucher, Dill, and Handy (2010); Millward, Spinney, and Scott (2013); Fishman (2016)).

Measures of ATB accessibility can either be location-based, focusing on the distances to opportunities from particular locations, or individual-based, taking into account the limitations of people’s time and space. This review focuses on location-based accessibility that is based on location. Vale et al (2016) categorized location-based accessibility measures into four main groups: first, activity-based, which includes gravity-based (also designated attraction-accessibility or potential) and cumulative opportunities measures (also known as isochrones or contour measures). In addition, this measure has been widely used in non-motorized accessibility studies (Iacono, Krizek, and El-Geneidy 2010; Lowry et al. 2012; Millward, Spinney, and Scott 2013; Prins et al. 2014; Li, Huang, and Axhausen 2020); second, topology infrastructure-based, which include topological measures of the network (Hull, Silva, and Bertolini 2012; Lundberg 2012); third, distance-based, which include analyses of the closest facilities (Apparicio et al. 2008; Sadler, Gilliland, and Arku 2011), and the last category being utility-based measures which are also known as benefits measures (Geurs and Van Wee 2004; Hunt and Abraham 2007; D. de S. Vale 2009; El-Geneidy and Levinson 2011).

potential compatibility with regional travel forecasting models is an essential reason for the wide use of location-based measures instead of individual-based measures for active transport mode. So, it is easy to extract travel times from one area to another area using the coded network. moreover, number of potential opportunities are available at the area level (Iacono, Krizek, and El-Geneidy 2010; Saghapour, Moridpour, and Thompson 2017).

There are some limitations of using these measures for active travel modes. first, active travel modes are less sensitive to travel times and levels of network congestion rather than motorized modes. as well, walking and cycling route choices tend to include qualitative, experiential, or difficult to measure factors (Hunt and Abraham 2007; Tilahun, Levinson, and Krizek 2007; Iacono, Krizek, and El-Geneidy 2010). second, measuring active transport accessibility is mostly dependent on travel diary data. besides, The methods applied so far to measure cycling accessibility have not focused on the accessibility of cycling destinations in terms of service areas (Landis, Vattikuti, and Brannick 1997; Harkey, Reinfurt, and Knuiman 1998; Harkey et al. 1998; Landis et al. 2003). some studies have investigated the level of services such as Bicycle Compatibility Index (BCI) or Bicycle Level of Service (BLOS) for a bicycle network. indeed, these measures focused on measuring the performance of a bicycle network using various geometric measures such as the width of the bicycle routes, pavement, route types, and connectivity. Nonetheless, there are other methods that consider bikeability in terms of how accessible different destinations are for bicycles as a transport mode. Such methods measure the potential for cycling using travel behaviour data (Espada and Luk 2011; Wahlgren and Schantz 2012; Rybarczyk and Gallagher 2014; Milakis et al. 2015).

##### Activity-based measures

Activity-based measures include both gravity-based (also known as Hansen-type (Hansen 1959) and cumulative opportunities measures. Gravity-based measures designated attraction –accessibility or potential and consider the number of opportunities weighted by the cost of traveling to them – using a travel impedance function that values closer opportunities higher. The same researchers underlined the importance of choosing a suitable impedance function and it can be observed that a large variety of functions are applied. Commonly used functions are power, negative exponential, logistic and Gaussian functions (Iacono, Krizek, and El-Geneidy 2010; Lowry et al. 2012; Vasconcelos and Farias 2012; D. S. Vale and Pereira 2017). More recently Vale and Pereira (2017) conducted a study testing 20 pedestrian accessibility measures and identified the modified Gaussian and exponential function as the most robust ones for modeling walking accessibility. Cumulative opportunities (also known as isochrones or contour measures), measures count the number of opportunities within a defined catchment area.

Gravity-based and cumulative opportunities measures are specific instances of a more general formulation (Páez, Scott, and Morency 2012):

This equation gives the accessibility from the origin location i, to opportunities of type k, from the perspective of individual p. This measure of accessibility is a function of the number of opportunities W of type k at location j, and the cost of moving between i and j as perceived/experienced by person p. Function f() defines a kernel around location i, usually symmetric if is given by Euclidean distance, but not necessarily, for instance if is measured over a network. Activity-based measures are useful when opportunities are complementary (e.g., jobs, people, services, parks) and when access to more opportunities and being closer (with gravity-based models) is advantageous.

##### Distance-based measures

Distance-based measures consider accessibility in terms of proximity, either by travel distance, time, or a generalized cost measure between locations. A distance measure analyses the closest facilities, including 1) distance to the closest opportunity, 2) the number of opportunities within a defined distance or time, 3) the mean distance to all opportunities, and 4) the mean distance to a defined number of closest opportunities (Apparicio et al. 2008). These measures are applicable when destinations are regarded as substitutes for one another (i.e., hospitals, transit stops, convenience stores etc.), under the assumption that individuals want to access the nearest facility.

Distance is considered as the travel impedance and four types of distances are usually used in distance-based accessibility measures: 1) Euclidean distance, that has been mainly used for walkability measures, particularly in health studies (Apparicio et al. 2008). 2) Manhattan distance, 3) shortest network distance (Lundberg 2012; Hochmair 2015) 4) shortest network time (Pearce, Witten, and Bartie 2006; Páez, Scott, and Morency 2012). As well, there are two different ways for measuring distance, first calculates the distance to the closest facility of each type. The first method calculates the distance from each zone centroid to the closest or the first n closest facilities (e.g. medical centers).and second, calculates the distance to all facilities close by. This approach is based on floating catchment areas that finds the closest facility regardless of distance and measures the distance from each zone centre to the closest or the first n closest different facilities (e.g. medical centres, shopping centres, etc.).

Distance to nearest location is calculated based on (1):

In this equation, is accessibility of zone i to location of type p, is set of locations of type p, and is distance (or travel time for a given mode) from i to location j in set . This measure is consistent with an extremely simple location model in which the nearest location is always chosen with probability 1.0. (2)

if ; = 0 otherwise

In equation 2, is the probability of choosing location j for purpose p given that one is located in zone i. This measure has two limitations, first, doesn’t consider the size/attractiveness of locations and second, doesn’t investigate the cumulative effect of multiple accessible locations. So, it is not recommended to calculate accessibility using this method as an independent measure.

##### Topological or infrastructure-based measures

Topological-based measures consider accessibility in terms of the street network, rather than access from origins to destinations. Topology measures may evaluate network connectivity, the quality of infrastructure within a catchment area, or some combination of connectivity and infrastructure quality. Indeed, this measure emphasizes on infrastructure evaluation. Such approaches are applicable in the context of planning – for example, in identifying priorities for development, or identifying potential impacts of redevelopment.

There are three types of topological measure: the first, this group evaluate the level of service (LOS) within a floating catchment area (FCA)(Sisson et al. 2006). The second type is similar the first one. however, this one used a pre-defined spatial unit to evaluate LOS, and this is based on the segment instead of the point (Emery and Crump 2011; Horacek et al. 2012; Lowry et al. 2012). The third one is very different, since traffic is not considered as a relevant parameter (Hoedl, Titze, and Oja 2010; Zielstra and Hochmair 2011; Jabbari, Fonseca, and Ramos 2021). These measures are based on and the evaluation of network segments, infrastructure characteristics, and include variables such as sidewalk or bike path availability, quality, and length among others.

##### Utility-based measures

utility-based measures evaluate accessibility based on individual preferences and the log-sum of discrete choice models applied to destination choice analysis (M. Ben-Akiva and Lerman 2021). This measure, which is known as benefits measures, can better represent individual accessibility than location-based measures. Utility-based measure can be calculated using two methods:

1. Assume that a decision-maker perceives the utility of a destination as: where is the individual’s idiosyncratic deviation in terms of how s/he perceives the utility of alternative j relative to the population average utility, . The person chooses the alternative that generates the maximum perceived utility, . Under very common assumptions, the probability that j is the maximum utility alternative and so is chosen is given by the multinomial logit (MNL) model(Train 2009):

In this equation, : The systematic utility of alternative j; is a Vector of explanatory variables and Β is a (Row) vector of parameters.

1. The actual perceived maximum utility is unobservable, but, for the case of the MNL model, it can be shown (M. E. Ben-Akiva et al. 1985) that the expected maximum utility associated with this choice is given by:

That is, it is the natural logarithm of the denominator of the logit choice model (sometimes referred to as the “logsum” term). Further, it can also be shown that this expected maximum utility is the consumer’s surplus for this choice. Thus it is a standard measure of economic benefit. Given this, Ben-Akiva and Lerman (1985) argue that it also provides a behaviourally and economically sound definition of accessibility: accessibility for a given activity is the expected utility that would be derived from participation in this activity, which is also the consumer surplus associated with this participation. That is:

In the following, Tables 1 and 2 have categorized recent studies based on the accessibility by walking and cycling. However, Vale et al. (2016) found relatively few studies examining cycling-specific accessibility in comparison to walking. For a comprehensive review of all 84 papers on walking and cycling accessibility (published by September 2013) refer to Vale et al. (2016).

**Table 1.** Studies employing cycling-specific accessibility measures

| **Type of metric** | **Study** | **Measure** | **Travel time / distance threshold** | **Origins / Destinations** | **Geographic scale** | **Travel time / distance calculation** |
| --- | --- | --- | --- | --- | --- | --- |
| Activity-based | Murphy and Owen (2019) | Cumulative job opportunities Access gap: comparing LTS 1-4 Weighted accessibility by a number of workers | 20 mins (Tested 5 to 6 mins) | Census block centroids | Neighbourhoods -> city level | Network travel time 15 km/h |
|  | Faghih Imani, Miller et al. (2019) | Cumulative opportunities: jobs & population access Calculated isochrones for LTS 1-4 | 30 mins | Dissemination area centroids | Dissemination areas | Network travel time |
|  | Wu, Lu et al. (2019) | Gravity-based measure: accessibility to POIS at metro stations Lognormal distance decay function (confirmed using distribution of bicycle-metro trip data) | 2.5 Km | Metro stations (origins) POIs (destinations) | 2.5 km buffer | Euclidean distance |
| Distance-based | Houde, Apparicio et al. (2018) | Proximity of bike paths: 1. Network distance to nearest section of cycling network 2.Network distance to cyclist-only bike path |  | Census tract centroids (origins) Bike paths (destinations) | Census tracts | Network distance |
|  | Pérez, Buck et al. (2017) | 1.the dedicated cycling network - The distance from census tract centroid to nearest bike network segment was measured to estimate the accessibility of each tract. 2. Level of traffic stress (LTS network) was used to assess accessibility in the district. |  | census tract centroid to nearest bike network | The District of Columbia | Euclidean distance |
| Topology-based | Mekuria (2012) | Network connectivity by LTS 1-4: percent trips connected percent nodes connected |  | Home-to-work O-D pairs from regional trip table Land parcel ‘attraction strength’ (size and land-use attraction) (destinations) | Census blocks | Network |

**Table 2.** Studies examining walking-specific accessibility

| **Type of metric** | **Study** | **Measure** | **Travel time / distance threshold** | **Origins / Destinations** | **Geographic scale** | **Travel time / distance calculation** |
| --- | --- | --- | --- | --- | --- | --- |
| Activity-based | Cheng, Caset et al. (2019) | Cumulative opportunities: chess/card rooms and urban parks for older and younger adults Park spaces weighted by their size | Adaptive distance thresholds (based on location and socio-economic variables) | locations from travel survey (origins) Parks and chess/card rooms (destinations) | Traffic analysis zones | Network distance |
|  | eyes, Páez et al. (2014) | Cumulative opportunities to urban parks for children parks spaces weighted by their size: 1. Accessibility based on all individual attributes from travel survey 2. Accessibility based on scenario profiles (gender, age, income,etc) | Based on statistical model of travel behavior | Locations from household travel survey Rasterized parks 25\*25 m (destinations) | Dissemination areas (weighted average) | Euclidean distance |
|  | García-Palomares, Gutiérrez et al. (2013) | Access quality indicator for metro stations: population served Access by age group Distance decay function by age group | 1500m & Distance thresholds calculated for different age groups | Metro stations (origins) Transport-zone level populations | 1500m metro station catchment areas | Network distance |
|  | Papa, Carpentieri et al. (2018) | Contour accessibility measure: bus catchment areas Number of inhabitants served by age group Catchment areas calculated with and without network slope | Dependent on frequency of bus service | Bus stops | Hexagonal cells 50m | Network distance Walking speeds dependent on age |

##### Walkability measures

Walkability indices can be defines based on the both the social and physical environment, a predictive indicator of active travel and physical activity to access facilities; based on indicator of the usability of the built environment to people (L. D. Frank, Andresen, and Schmid 2004; L. D. Frank et al. 2006) who walk to different destinations and for different purposes (i.e., from a clear origin to a clear set of destinations) (Saelens and Handy 2008; Blečić et al. 2015; D. S. Vale, Saraiva, and Pereira 2016; Dovey and Pafka 2020). There is a difference between gravity- and distance-based accessibility measures and the walkability index so that for measuring walkability, area characteristics around the origins and destinations are also taken into account in the calculation, but still, this index does not consider route characteristics.

Walkability measures are divided into 4 categories including Frank’s Walkability Index, Walk score, Objective Walkability Index (OWI), and Graz Walkability Index. In the Frank’s index, a walkability score is calculated by summing the normalized scores across factors that are identified based on a definition of the concept of walkability. This index uses residential density, land use mix, retail floor area ratio, and intersection density as variables to measure walkability. Then Grasser, Van Dyck et al. (2013) improved Frank’s index for assessing Europe cities by considering population density, household density, and entropy index for land-use mix, and three-way intersection density in order to construct the Graz walkability index (Grasser et al. 2013). In addition, some other theory-based methods such as Objective Walkability Index (OWI) are also proposed. Weiss, Maantay et al. (2010) constructed the OWI, which includes street connectivity, land use mix, pedestrian safety, neighborhood aesthetics, neighborhood safety, and neighborhood infrastructure(Weiss, Maantay, and Fahs 2010). In 2011, Duncan, Aldstadt et al. (2011) developed Walk Score for measuring walkability of neighborhoods. Indeed, Walk Score recognizes eight types of walking attractors: Errands, Culture, Grocery, Park, Dining and Drinking, School, and Shopping. Walk Score can be assessed for any location worldwide, however, locations outside the US, Canada, Australia, and new zealand should be additionally validated, since the geolocated data is not always complete [Duncan et al. (2011); WalkScore 2020].

most of the studies assessed walkability using two Frank’s index and walk score (L. D. Frank et al. 2005, 2006, 2010; D. S. Vale, Saraiva, and Pereira 2016). The major difference between these approaches is that Walk Score uses a gravity-based methodology. Opportunities are weighted using a distance decay function, while the Walkability Index is based on a cumulative opportunities measure. In the following, Table 3 provides a summary of this categorization.

**Table 3.** Studies examining walkability

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Methods** | **Author** | **Variables** | **Data** | **Descriptions** |
| Methods based on a theory-driven approach |  |  |  |  |
| Frank’s Walkability Index | Frank, Schmid et al. (2005), Frank, Sallis et al. (2010) | · Net residential/ Population density | · travel data from both Census Journey to Work for both regions |  |
|  |  | · Retail floor area ratio | · Household Travel Survey Data |  |
|  |  | · Intersection density | census-based demographic data |  |
|  |  | · Land use mix |  |  |
|  | Manaugh and El-Geneidy (2011) | · Net residential/ Population density | · Retail information (shopping and school) was obtained from the Dun and Bradstreet business database and combined with a weighted intersection index. | · nine models were generated for each trip purpose using a different walkability measure in every run (Walkscore, walk opportunities, the WI at four scales and three sizes for the pedshed connectivity measure) |
|  |  | · Retail floor area ratio | · used a database of over 100,000 postal code points from Walkscore.[1] | · The walkability index generated at four scales: 400, 800 and 1200 m network buffers as well as at the census tract level. |
|  |  | · Intersection density | · Household level data and travel behavior characteristics are obtained from the 2003 Montréal Origin–Destination survey. | · used a simple gravity-based measure to weight nearby locations higher than those more distant. |
|  |  | · Land use mix | · census tract level demographic data derived from Statistics Canada |  |
|  |  |  |  |  |
|  | Adhikari, Delgado-Ron et al. (2021) | · residential density | · demographic characteristics of participants | · The walkability index uses 1 km pedestrian “walksheds” that map pedestrian-accessible roads around each postal code centroid. |
|  |  | · the commercial floor-to-area ratio |  | · Each walkshed corresponds to approximately 10–15 min of walking time, a commonly used time frame to assess perceived proximity to amenities and services. |
|  |  | · land-use mix |  |  |
|  |  | · intersection density |  |  |
|  | Azmi, Karim et al. (2013) | · Mixed-use planning | · data was gathered by using the questionnaire survey | · the type of community facilities or services selected was based on the availability of the services provided within a radius of 400 meter (approximately 5 minute of walking) |
|  |  | · Density | · asking the accessibility of residents walk from their home to community facilities or services provided within the walkable catchment | · There are a total of 13 community facilities and services such as grocery store/supermarket, park or recreational facility (indoor or outdoor), elementary school, other school, community center, restaurant or other places, bank, medical clinic/pharmacy, personal shop (laundry, salon), workplace, bus stop, post office and place of worship. |
|  |  | · Street connectivity | · indicated the amount of time they thought it would take for them to walk from their home to the nearest destination. |  |
|  | Liao, van den Berg et al. (2020) | · The variables of this section are divided into four parts: | · as a source of walking frequency data, the Dutch national travel survey. | · density variables: population density, intersection density, and business property density |
|  |  | ü density | · neighborhood data as a source for socio-demographic and physical neighborhood variables and used as control variables include gender, age, income status, work status, household status, and migration background. | · facilities variables: a range of facilities the distance to the nearest facility (average distance from the center of the neighborhood) and the number of facilities available within a 1 km radius (from the center of the neighborhood) |
|  |  | ü facilities | · All walkability variables were derived from the Esri-open postcode plane and the CBS data. | · green space variables: total area of different types of open green space and recreational space. |
|  |  | ü green space |  | · land use mix variables: the separate lower-level land-use variables in the form of a percentage of the total land covered by the land-use were used |
|  |  | ü land use mix |  |  |
|  | Arellana, Alvarez et al. (2021) | · intersection density | · latest household Origin Destination survey. | · Calculated potential accessibility. |
|  |  | · land use entropy score | · Land use data, the location of commercial zones, the population, and the characteristics of the walking trips from each zone (TAZ). | · The measure evaluates the access to shop, job, study, and institutional opportunities |
|  |  | · population density |  |  |
|  |  | · commercial density |  |  |
|  | Ruiz-Padillo, Pasqual et al. (2018) | · Public Security | · Census tracts were used that including size and number of households | all census tracts were classified according to three variables: |
|  |  | · Traffic Safety |  | ü motorization rate |
|  |  | · Convenience and attractiveness: |  | ü density of commercial and service establishments |
|  |  | ü Street connectivity |  | ü average slope |
|  |  | ü Destination’s proximity (number of shops and services) |  |  |
|  |  | ü Mix of uses proximity (number of shops and services) |  |  |
|  |  | ü attractiveness |  |  |
|  |  | · Characters of the roots: |  |  |
|  |  | ü Pavement Quality |  |  |
|  |  | ü Pavement width |  |  |
|  |  | ü Slope |  |  |
| Walk Score (Walk Score calculates a score by determining the walking distance to amenities in nine different amenity categories) | Duncan, Aldstadt et al. (2011) | · Walking distance to amenities | · Google AJAX Search application program interface (API) provides data for the Walk Score. |  |
|  |  | · Intersection density metrics |  |  |
|  |  | · Average block length |  |  |
| Graz Walkability Index (based on American city and Frank’s walkability index) | Grasser, van Dyck et al. (2017) | · Net residential/ Population density/ household density | · Outcome data were derived from the representative cross-sectional survey | present study reported the results of the 1000 m circular buffer and the 1500 m street network buffer[2]. |
|  |  | · Intersection density | · Walking (for at least 10 min) and cycling (in the warm season) |  |
|  |  | · Land use mix (entropy index for land-use mix) |  |  |
|  |  |  |  |  |
|  |  |  |  |  |
| [1] Walkscore.com. |  |  |  |  |
| [2]most studies (conducted mainly in USA and Australia) use 1000 m buffers. The European environmental questionnaire ALPHA used a distance of 10- to 15-min walk (i.e. \_1–1.6 km) as a neighborhood scale. |  |  |  |  |
|  |  |  |  |  |

##### Bikeability measures

Bikeability can be defined as the ability of a person to bike or the ability of the urban landscape to be biked or as a baseline definition of the likelihood that individuals or groups of people will choose the bicycle as a mode of transport or leisure (Krizek, Handy, and Forsyth 2009; Winters et al. 2013; Nielsen and Skov-Petersen 2018) .However, It should be noted that the bikeability index described by several scientists: in 2012, Lowry, Callister et al explained the Bikeability index as the comfort and convenience of an entire bikeway network for accessing important destinations. Then they referd that this index is the only methodology exclusively dedicated to bicycle travel (Lowry et al. 2012). In additional, The Bikeability Index described by Winters, Brauer et al. (2013)includes the three basic measures, but adds the length of bicycle routes, slope, and the separation from car traffic. Each variable is given a score of 1 to 10, which is then summed to produce the final score (Winters et al. 2013).

Explaining the Bikeability of an environment has included the following characteristics:

* Single principles of the townscape or the infrastructure, such as bicycle tracks, crossings, and parking facilities, which are referred to by Lowry, Callister et al. (2012) as “bicycle suitability”(Lowry et al. 2012).
* Neighbourhoods are delineated based on airline/Euclidean distance rather than network distance (Greenberg and Renne 2005; Nielsen and Skov-Petersen 2018)
* Explicit polygon features generated around specific trajectories of individual respondents – e.g., as recorded by GPS. Such features can be purely geometric, such as buffers or ellipsoids, or be based on the topology of a transport network (Madsen et al. 2014; L. D. Frank et al. 2017).
* Connected infrastructures as a functional component of entire towns and urban fabrics (Lowry et al. 2012). According to Lowry, Callister et al. (2012), this is in fact what covers the term “Bikeability”. In the following, Table 4 prepares some of the studies that used bikeability index.

**Table 4.** Studies examining bikeability

| **Author** | **Study area** | **Measure** | **Data** | **Descriptions** |
| --- | --- | --- | --- | --- |
| Lowry, Callister et al. (2012) | Moscow, Idaho | · proposed calculation for bikeability was developed on the basis of a common accessibility equation (Hansen’s model). | · bikeway is any roadway where bicycle travel is permitted regardless of the presence of a bike lane | · Assessment of bikeability considers comfort and safety of the entire bikeway network for access to important destinations. |
|  |  | · calculation finds the shortest routes between zone i and every destination j | · Complete entire bikeway network and important destinations in the case study community | · impedance functions were estimated based on a negative exponential function. |
|  |  |  | · only arterials, collectors, and shared-use paths were considered part of the major bikeway network. | · bikeability was assessed for all commercial destinations |
| Nielsen and Skov-Petersen (2018) | Denmark | · presented a micro-level analysis of the Bikeability variables included density/accessibility, | · cycling data obtained from the Danish National Travel survey |  |
|  |  | infrastructure provision and terrain measured | · a classification of all roads and paths into seven classes is provided: roads without bicycle infrastructure, roads with bicycle lanes, roads with bicycle paths (protection by kerb and/or separating strip), fully separated bicycle and foot paths, fully separated foot paths, roads without access for pedestrians or bicycles, and roads without public access. | · The survey’s account of cycling includes cycling as the main mode of transport as well as cycling as a stage mode, e.g., connecting to public transport and leisure cycling without a destination purpose. |
|  |  | · The accessibility was based on the shortest path network distance from trip origins. | · the number of residents, jobs, retail jobs, schools, high schools, and further education were counted within 1 km, 2 km, 3 km, 4 km, and 5 km of each trip origin and added to the travel survey dataset. | · The average slope of the terrain within the same distances (Euclidian measure) was applied. |
|  |  |  |  |  |
| McNeil (2011) | Portland, Oregon | · assessing a neighborhood’s bicycle accessibility or “bikeability” on the basis of 20-min neighborhood for bicycles. | · the 2009 National Household Transportation Survey | · this research focused on home-based utilitarian trips and excluded any trips to and from work. |
|  |  | · Using a scoring method in order to assessment the bikeability, | · Geocoded data for parks, schools, libraries, and transit connections (light rail stops and bus lines) were obtained from Metro’s Regional Land Information System. | · Business addresses were gathered and geocoded for all childcare providers, grocery stores, clothing stores, general goods stores, beauty services (e.g., salons, barbers), banks, mail services (e.g., post offices, private mail providers), laundries and cleaners, gyms, general entertainment (e.g., bowling, performance venues), drinking establishments, movie theaters, restaurants, coffee and snack shops, and religious organizations. |
|  |  |  | · Business address data for other destination types were acquired through a data clearinghouse, Reference USA. |  |
|  |  |  |  |  |
| Saghapour (2017) | · | · Introducing a new index for measuring bikeability; | database included urban centres, significant buildings, landmarks, public spaces, community facilities and indigenous locations.- considered as destinations and categorized into four groups of activities. | · Service area and OD-cost matrix analysis was undertaken for each set of destinations separately: |
|  |  | Cycling Accessibility Index (CAI) was developed for quantifying cycling accessibility using the travel distance as impedance along with cycling catchments within local areas in metropolitan area | ü A datab`ase of Mesh Blocks from the 2011 Census and contained the total usual resident population and total number of dwellings. | · 4 km buffers were calculated for education centres and health and care facilities |
|  |  | Using gravity-based measures of accessibility. | · Point of Interests (POIs): | · used the median desirable travel time/distance |
|  |  | · Network models are applied to identify acceptable cycling catchments as well as an Origin-Destination (O-D) cost matrix | ØEducation Centres | · uses the speed of 16 km/h which has been adopted from the Austroads network operation planning framework |

## A framework for assessing data sources and needs

For calculating accessibility in active transport mode, multiple data sources are required. Following a review of the relevant literature, it was discovered that various data sources such as Travel data (trips), Users data (Socio-economic and personal data), Origin- destination, Cycling and walking network, Spatial data (boundary, land use, postal code, . . . ), additional data (such as Traffic data, weather data, slope, Level of Traffic Stress, impedance value, speed ) are required in order to determine the accessibility of active transportation.

A particular kind of data management system is a data warehouse. Data warehousing is a topic that includes application tools, architectures, information services, and communication infrastructures to combine information from disparate heterogeneous operational data sources that is valuable for decision-making. This data is collected into a single repository known as a data warehouse (DW), which may be used for direct querying and analysis, and as a source for creating logical data marts focused on particular parts of the organization (Kimball and Ross 2011). Important data for decision making is often retrieved from the organization’s data sources, processed (i.e., cleaned and homogenized), and then integrated within a sizable data repository (the data warehouse), in what is known as the ETL (extraction/transform/loading) process (Romero and Abelló 2010).Inconsistent data, incompatible data formats, data granularity, and other common problems with distributed heterogeneous information services are covered in the first phase (for instance, see (Zhuge, Garcia-Molina, and Wiener 1996)).Regarding the second step, creating the DW necessitates methodologies entirely distinct from those used for operational information systems.In this article, the approach used to design the data warehouse is based on the multidimensional paradigm.The fact/dimension dichotomy serves to distinguish the multidimensional view of data, which is characterized by its representation of data (i.e., the relevant fact) as though it were in an n-dimensional space (with as many axes as dimensions of analysis of interest). This paradigm makes it simple to comprehend and evaluate data illustrating the various angles from which a subject may be examined. As a result, the multidimensional model is appropriate for non-expert users such as knowledge workers (from here on, the data warehouse end-users).The third phase needs for the ability to leverage aggregate navigation (Gupta, Harinarayan, and Quass 1995), complex query optimization (Chaudhuri and Shim 1994), advanced indexing strategies (Lomet and Salzberg 1990), and user-friendly visual user interfaces for OLAP (On-line Analytical Processing) (Chaudhuri and Dayal 1997; Colliat 1996) and data mining (Fayyad, Piatetsky-Shapiro, and Smyth 1996).

In this study, the multidimensional data warehouse design and end-user requirements elicitation tasks are supported by a user-centered methodology. Three steps make up the process:

First, our method begins by thoroughly examining the data sources to determine, without yet taking requirements into consideration, the multidimensional knowledge they capture (i.e., data likely to be analyzed from a multidimensional point of view).

Second, we suggest using this knowledge to aid in the work of needs elicitation. By doing this, we are able to fully utilize the sources’ analytical skills while already balancing requirements with the data sources.

Third, once the requirements are established, we automatically generate the data warehouse conceptual schema and the multidimensional knowledge extracted from the sources.

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Table 5, shows required data based on the each measure.

**Table 5.** Required data according to each measure

| **Data / Methods** | **Travel Data** | **Users Data** | **Origin- destination Data** | **Cycling and walking network** | **Spatial data** | **additional data** |
| --- | --- | --- | --- | --- | --- | --- |
| Activity-based | Travel data is usually obtained from surveys and includes information about each trip such as duration, start point, end point, origin and destination. | travel behavior characteristics such as age, gender, income, can be considered if the data are available | The origin and destinations spatial data or a database of POIs that is obtained from local map. Indeed, a database of POIs consists of the location of all of the facilities such as home, workplace, parks, schools, groceries, etc. | Walking and cycling network data are required for calculating time or distances (using network analysis or nearest distance) that can be obtained from both the OpenStreetMap and the local government data portals. | spatial data of statistical areas such as blocks, mesh, zones, areas, etc. This data set includes some information such as population, number of dwellings, employment data, etc. This dataset is required for calculating accessibility in each area. | · Impedance functions are required that are usually estimated based on a negative exponential function and it is mostly based on the travel time. |
|  |  |  |  |  |  | · Slope can be considered for calculating accessibility. |
| Distance-based | —– | —– | Required to calculating the shortest distance to nearest facilities. | Required to calculating nearest distance or time to facilities using network analysis. | Required to census tracts data. |  |
| infrastructure-based | —– | —– | —– | Walking and cycling network data are required | Spatial data of essential services or origins/destinations are required. For example, grocery stores, hospitals, schools, bikeshare systems etc |  |
| Utility-based | Travel data is required. | travel behavior characteristics are required such as age, gender, etc. | —– | Walking and cycling network data are required | Spatial data of essential services |  |
| Walkability | Travel data is usually obtained from surveys and includes information about each trip such as duration, start point, end point, origin and destination. | travel behavior characteristics are required such as age, gender, income, car availability and etc. | The origin and destinations database is required | Walking and cycling network data are required | Spatial data of net residential/ Population density, Retail floor area, Intersection density, and Land use mix are required |  |
| Bikeability | Travel data is required and includes information about each trip such as duration, start point, end point, origin and destination. | - | The origin and destinations database is required . | Walking and cycling network data are required for calculating time or distances (using network analysis or nearest distance) | spatial data of statistical areas such as blocks, mesh, zones, areas, etc. is required for calculating accessibility in each area. | Impedance functions are required that are usually estimated based on a negative exponential function and it is mostly based on the travel time. |

## Data needs and sources

**Travel data (trips)**

Travel data provides information about the trips, including the mode of travel, duration of travel, and trip origins and destinations. This data can obtain from General social survey (GSS) for all over the Canada. The (GSS)-time uses is conducting every 5 years and the last survey was done in 2015. This survey monitors changes in time use to better understand how Canadians spend and manage their time. This dataset contains travel time data of Many of the Census Metropolitan Areas (CMAs) and non-CMA areas all over Canada. CMAs are including St. John’s, Halifax, Saint John, Montreal, Quebec City, Toronto, Ottawa, Hamilton, Winnipeg, Regina, Saskatoon, Calgary, Edmonton, and Vancouver. and the non-CMA areas of each of the ten provinces were also grouped to form ten more strata. In addition, this dataset contains 301 bicycle and 4236 walking trips. Each trip contains pumID, start time, end time, duration, origin and destination.

In addition to the general social survey, travel time data can be obtained for the cities of Toronto and Montreal from the Transportation Tomorrow Survey (TTS) and the Autorité régionale de transport métropolitain (ARTM) survey. The 2016 Transportation Tomorrow Survey (TTS) was conducted on behalf of 22 local, regional, provincial and transit operating agencies in Greater Toronto and surrounding regions. the TTS database for the city of Toronto includes Travel data (e.g., mode, trip length), personal data (e.g., age, gender), household data (e.g., number of persons, income), and transit data (e.g., access distance, access mode to transit). As well, the Autorité régionale de transport métropolitain (ARTM) is an origin-destination survey and one of the most critical transportation studies in Quebec that has been carried out every five years since 1970. Data are collected for each household (home location, size, number of cars), each person in the household (age, gender, driving license ownership, main occupation, public transit monthly pass ownership), and each trip made by each person of 5 years and older (departure time, origin and destination locations, trip purpose, mode sequence, and others).

**Users data (Socio-economic and personal data)**

Demographic variables of users including age, gender, and the number of households can be obtained from General Social Survey (GSS) in 2015. In addition, the Statistics Canada population census provides a statistical overview of various geographic areas all over Canada such as provinces and territories, census metropolitan areas (CMAs), census agglomerations (CAs), Census divisions (CDs), etc in 2021 and includes different variables for example number of population, age, and gender **(StatisticsCanada 2021)**

**Origin- destination data**

Various articles examine bicycle and walking trips to different purposes. the most important destinations are educational facilities, cultural and Art Facilities, recreational and Sports Facilities, healthcare facilities, grocery stores and markets, services and government offices (such as banks, post offices, and insurance company, etc ), work, and home. Origins and destinations data of cycling and walking trips all over Canada can be obtained from two sources of General Social Survey (GSS)-time uses data and The Linkable Open Data Environment (LODE).

In the GSS database, different travel destinations and locations are considered and each location is identified with a specific code, as follows: home or on the property, someone else’s home or property, work or school, in the neighbourhood, Outdoors, Grocery store, other stores or mall, Library, museum or theatres, Sports center, field or arena, Restaurant, bar or club, Place of worship, medical, dental or another health clinic, and Elsewhere.

In addition, the Linkable Open Data Environment (LODE) is an exploratory initiative that aims at enhancing the use and harmonization of open microdata primarily from municipal, provincial and federal sources. It has been compiled by the Centre for Special Business Projects (CSBP) at Statistics Canada in 2020. This database includes variables such as address, postal code, city, province and latitude and longitude of each facility and includes a Canada-wide Open Database of educational facilities (this database covers facilities such as early childhood education, kindergarten, elementary, secondary, and post-secondary institutions, and specific vocational training centers. The database does not include virtual educational institutions.), healthcare facilities (including ambulatory health care services, hospitals, and nursing and residential care facilities), cultural and art facilities (such as arts or cultural centers, artists, festival sites, galleries, heritage or historic site, library or archive, museum, theatre/performance and concert hall, and miscellaneous), and recreational and sports facilities (including trails(such as urban and rural trails or pathways for walking, hiking, or biking), sports fields, arenas (facilities where sports and/or recreational activities take place), athletic parks, beaches, casinos, community centers, gyms, marinas, parks and green spaces, playgrounds, pools, race tracks, ice rinks, skate parks, splash pads, stadiums, miscellaneous), and Businesses (this database contains addresses of business, name, type of business and locations).

**Cycling and walking networks**

Cycling and walking networks can be obtained from different sources such as Can-BICS, open street map (OSM), and municipal open data.

Can-BICS is a classification system of five broad bicycle facilities assigned to three categories: high, medium, and low comfort, based on the facility’s contribution to user safety and comfort while cycling. 1) High comfort includes low-stress routes that are comfortable for most people, including those of all ages and abilities, with a record for best safety. for example, cycle track, local street bikeway, and bike path. 2) medium comfort is low- or medium-stress routes that are comfortable for some people, but whose safety requires careful design, such as multi-use paths (A two-way paved path shared by cyclists, pedestrians and other users). 3) low comfort bikeways are high-stress routes that are comfortable for few people, with little or no additional safety, compared to no bicycle facility, such as painted bike lanes that are designated by bicycle and diamond pavement markings and signs as exclusively for cyclists. And 4) non-conforming bicycle facilities do not meet minimum Can-BICS standards, such as non-conforming - trail (these are multi-use trails with unpaved surface), non-conforming – major road (shared lanes on major roads provide connectivity), and non-conforming - other.

Can-BICS measured bicycle infrastructure for all communities in Canada, at the neighborhood level, using open data sources such as OpenStreetMap (OSM). This data was completed in 15 pilot cities such as Edmonton, Ottawa, Montreal, Vancouver, Winnipeg, Halifax, Regina, Saint John, Victoria, Canmore, Cornwall, Courtenay, Whistler, and Whitehorse.

Another source for obtaining cycling and walking networks is OpenStreetMap (OSM). This dataset is a collaborative global map that using for active transportation researches. OSM considered cycle lanes, tracks and sidewalks. A cycle lane lies within the roadway itself (on-road), whereas a cycle track is separate from the road (off-road). Tracks are typically separated from the road by e.g. curbs, parking lots, grass verges, trees, etc. as well, trails line that indicates the paths or routes suitable for walking, hiking, bicycling, and other outdoor activities from 2015 to 2019 can be obtained from scholars Geoportal.

As well, municipal open data is a standard source of bicycling infrastructure data that city governments are making this spatial data for bicycling infrastructure. In Canada, some cities have this dataset such as Toronto, Montreal, Vancouver, etc. However, open data of different cities use different definitions for bicycling infrastructure, and they may have different levels of timeliness, completeness, and documentation (Schoner and Levinson 2014). For example, bicycle facilities the City of Toronto Open Data portal consists of a high-resolution geospatial data set with attributes accumulated from several sources of cycle tracks or bike lanes, road classification (local, collector, minor arterial, etc.), number of lanes, directions, stop signs and signalized intersections. (City of Toronto, 2017).

**Spatial data (boundary, land use, postal code, etc)**

Spatial data such as boundary, land use, postal code, origin and destinations and etc can be obtained from scholars Geoportal and open street map (OMP).

scholars Geoportal has different shape file layers such as Land Cover Region (including seven land use categories: commercial; government and institutional; open area; parks and recreational; residential; resource and industrial; or waterbody in 2019), education Point (includes the point locations of elementary schools, high schools, colleges, cégeps and universities in 2020.There is also additional information about teaching languages and grade levels), enhanced Points of Interest (EPOI) in 2019, which indicates the locations of business and recreational points of interest across Canada in 2020, Healthcare (HCR) that contains the location of hospitals, long-term care facilities, outpatient clinics, nursing stations, and community health centres in 2020, Tourist Attractions Point that indicates the point locations for various tourist sites (such as National, Provincial, and Municipal parks, Art Galleries, Historic Sites, Museums, Science Centres, Tourist Information Booths, and Zoos) in 2020, Park sports field point in 2019 across Canada, Cinemas Point, Religious Buildings Point, Retail Point that indicates the locations shopping centers and department stores in 2020, and accommodations Point such as hotels, motels, campgrounds, inns, hostels, resorts, etc., in Canada.

## Important considerations and possible challenges

**Travel time/distance thresholds**

Selecting an appropriate cut-off distance for travel has been acknowledged as an important step that has the potential to significantly impact results. Different distance thresholds should apply to both cycling and walking, however, there remains considerable variation among the threshold values applied within each mode.

Some analyses choose to vary thresholds according to the destination type, or by population group. For example, Saghapour (2017) use a 10-minute travel time for retail and recreation centres and a 20-minute travel time for cycling to community services(Saghapour, Moridpour, and Thompson 2017). Applying the same threshold to all age groups also disregards the fact that certain groups (for example, seniors and children) may travel slower or require greater effort to travel the same distance. Although applicable to both cycling and walking, this distinction by age group has only been applied among walking measures. In the following, Tables 5 shows the thresholds of bicycle and walking travel time and distance in different studies.

**Table 6.** Thresholds of bicycle and walking travel time and distance

| **Distance/Time thresholds** |  |
| --- | --- |
| **walking trips** |  |
| Neilson and Fowler (1972), O’Neill, Ramsey et al. (1992), Hsiao, Lu et al. (1997), Murray and Wu (2003), Zhao, Chow et al. (2003), Kimpel, Dueker et al. (2007), Gutiérrez and García-Palomares (2008) | The most common standard measure of walking distance to transit stops and stations has been 400 m (0.25 miles). |
| Lam and Morrall (1982) | In Calgary, Canada, observed a median walking distance to bus stops of 292 m, while the average was 327 m and the 75th percentile, 450 m. |
| O’Sullivan and Morrall (1996) | distinguished between walking to light-rail transit stations in the suburbs and in the central business district. They found an average distance of 649 m and a 75th percentile equal to 840 m in the former, while the average distance was 326 metres and the 75th percentile was 419 metres in the latter (Calgary, Canada) |
| Arasan, Rengaraju et al. (1996) | an average critical trip time is 20 min for walking. |
| Nicholls (2001), Smoyer?Tomic, Hewko et al. (2004) | used a distance of 0.8 km as a reasonable threshold for walking trips (the threshold is not specific to a population group) |
| Zhao, Chow et al. (2003) | in southeast Florida, the number of riders walking over half a mile (800m) was negligible. |
| Van Herzele and Wiedemann (2003) | Maximum distance from home to: 1) Residential green (150 m); Neighborhood green (400 m); Quarter green (800 m); District green (1600 m); City green (3200 m); Urban forest (5000 m) |
| Tsou, Hung et al. (2005) | Defined varying distances that depended on the type of facility: |
|  | · the service range of municipal facilities such as town parks, universities, museums and dump sites cover the entire city. |
|  | · community facilities, including junior and senior high schools, transformer stations, etc., are typically in the 2 km range. |
|  | · The service range of neighborhood facilities like playgrounds and elementary schools is typically in the 1 km range. |
| Schlossberg, Agrawal et al. (2007) | walking distances to rail transit stations in Portland, WA, and San Francisco, were a median distance of 0.47 miles (756 m) |
| Alshalalfah and Shalaby (2007) | showed that among transit users, 60 % live within 300 m from their stop and 80 % within 500 m in Canada. |
| Larsen and Gilliland (2008) | Population within 500 m walk distance of supermarkets |
| Manaugh and El-Geneidy (2011) | used 400, 800 and 1200 m thresholds for calculating walkability score |
| Daniels and Mulley (2013) | the mean walking distance to bus service 461 m with 75th percentile at 566 m. |
|  | In the same study they found mean walking to rail around 805 m and the 75th percentile at 1,018 m. |
|  | Also, it is clear that these distances are significantly beyond the 400 m for buses and 800 for rail. |
| El-Geneidy, Grimsrud et al. (2014) | The 85th percentile walking distance to bus transit service is found to be around 524 m for home-based trip origins, 1,259 m for home-based commuter rail trip origins. |
| Azmi, Karim et al. (2013) | considered radius of 400 meter (approximately 5 minute of walking) in the neighborhood area. |
| Saghapour (2017) | considered 20-30 mins or 1.6 – 2.4 km (Based on POI type) |
| van Soest, Tight et al. (2020) | 400 or 800 m thresholds for walking to public transport |
| Adhikari, Delgado-Ron et al. (2021) | 10–15 min of walking time, a commonly used time frame to assess perceived proximity to amenities and services |
| Cycling trips |  |
| Arasan, Rengaraju et al. (1996) | found an average critical trip time of 24 min for bicycling. |
| Seneviratne (1985), Arasan, Rengaraju et al. (1994), Rastogi and Krishna Rao (2003) | proposed an average critical distance of 1100 m across the categories of trip type, and 1050 m and 750 m respectively for the categories of male and female. |
| Houde, Apparicio et al. (2018) | access to the cycling network within a 500-metre radius and the access to a cyclist-only bike path within a 500-metre radius from the centroid of the census tract. |
| McNeil (2011) | the average cyclist would be willing to travel between 1 mi and 2.5 mi for most utilitarian nonwork trips |
| Saghapour (2017) | Considered 10-20 mins or 2.5 - 4km (Based on POI type) |
| Tucker and Manaugh (2017) | A cut-off length of 7 km was used. |
| Manum, Nordstrom et al. (2019) | a travel-time threshold of 15 minutes in one direction is a reasonable value for calculating the catchment area. (bicycling speeds vary) |
| Faghih Imani, Miller et al. (2019) | calculated the 30-minute cycling thresholds to accessibility to jobs |
| Li, Huang et al. (2020) | consider the trips whose trip distance and duration are between the 1st (301m and 180 s) |
| Chen and Wang (2020) | five thresholds (10-, 20-, 30-, 45-, and 60-minute) by cycling. |
| Mora, Truffello et al. (2021) | Access to bicycle lanes from the blocks was modeled in consideration of three critical distances: 300 m, and 500 m or 1000 m (Average minimum distance to bicycle lane) |

**Impedance functions**

Impedance function is used to describe willingness of cyclists and pedestrian to travel to a destination as a function of cost (distance, time, etc.); it is a component of accessibility (Iacono, Krizek, and El-Geneidy 2010; Yang and Diez-Roux 2012; Arranz-López et al. 2019). The impedance function obtained by fitting to a real dataset provides a continuous description of cycling and walking probability at different costs. The spatial distribution of bicycle and pedestrian travel can be expressed using distance decay functions (Iacono, Krizek, and El-Geneidy 2010) as travel distance is a limiting factor for implementing use(Larsen and El-Geneidy 2011). Distance decay functions describe the effect of distance on spatial interactions and typically express distance as a function of travel impedance (time or cost). Rybarczyk and Wu (2010) identified the importance of the spatial patterns of bicycle facilities and connectivity of a local network when studying accessibility. Furthermore, increased connectivity within a network also allows for increased accessibility(Rybarczyk and Wu 2010).

Some researchers have argued that – like maximum travel thresholds – distance-decay rates should differ according to trip purpose and different population groups (Garcı́a-Palomares, Gutiérrez, and Cardozo 2013; X. Wu et al. 2019). Similarly, researchers also argue that walking and cycling impedance functions should be calculated separately due to their differing travel speeds and maximum travel ranges (Cheng et al. 2019). For example, the distance-decay curve for work trips shown in Figure 1 assumes that cyclists are half as likely to reach a work destination 20 minutes away than one 10 minutes away, and therefore, any jobs 20 minutes away would be applied half the weight of jobs 10 minutes away. These cycling weights differ slightly from walking trips since fewer people are willing to walk a longer distance to work. While adjusting the distance-decay functions by mode has the potential to improve accuracy, it can also be said that a consistent approach to measuring accessibility across modes is preferable due to the possibility of causing one mode seem less accessible when applying different decay functions (State Smart Transportation Initiative, 2021).

In terms of the types of impedance functions considered, a negative exponential curve is common (Saghapour, Moridpour, and Thompson (2017); X. Wu et al. (2019)] – example shown in Figure 1. However, some studies have also calculated study-specific distance-decay curves based on trip data rather than assuming a standard function. Wu, Lu et al. (2019) calculated a distance-decay function using data from Shenzhen’s dockless bicycle-sharing system. Their findings show that a lognormal distance decay best fit the distribution of bike-sharing trips, with the willingness to cycle increasing up to ~500m and decreasing thereafter. García-Palomares, Gutiérrez et al. (2013) took a similar approach for measuring walking accessibility to metro stations and found a linear distance-decay trend that varied significantly by age (Garcı́a-Palomares, Gutiérrez, and Cardozo 2013; X. Wu et al. 2019).

|  |
| --- |
| Figure 1: Example travel time decay functions by mode for work vs. non-work trips. (Source: State Smart Transportation Initiative - based on data from 2017 National Household Travel Survey) |

**Slope**

One of the factors associated with the natural environment and has an effect on bicycle and walking trips is slope. hence, pedestrians and cyclists will travel out of their way to by-pass segments with steep slopes. because, For them, small positive increments in slope decrease travel speeds while increasing energy use and travel time. Besides, due to the differences in efforts to go up-slope versus down-slope, pedestrians and cyclists may not select the same way. This is referred to as anisotropic movement (Ebener et al. 2005).

There are few studies that have considered slope in measures of active accessibility, yet it is acknowledged as an important factor to include since people will often avoid routes with significant elevation gain, and routes with steep slopes may significantly impact accessibility. Often, network analyst tools use the shortest path from the road network, which may not reflect actual cycling or walking behavior. Vale, Saraiva et al. (2015) concluded that slope should always be included in accessibility of bicycling and that it is also important for walking, however it is largely absent from walking accessibility measures (D. S. Vale, Saraiva, and Pereira 2016). However, the greater availability of elevation data and advances in research in various disciplines offer opportunities to better understand the behavior of individuals when travelling in infrastructure-poor contexts and challenge assumptions surrounding the most important costs to be minimized. Papa, Carpentieri et al. (2018) also highlighted a significant difference in catchment areas when including versus excluding the slope attribute (~33% km2 difference for adults over 75) (Papa, Carpentieri, and Guida 2018). Wood, Jones et al. (2018) studied the sensitivity in distance calculation to variations in three travel-time modeling approaches, taking as reference a model that accounted for variations in land cover and directionality in slope (anisotropy). They found that an approach based on measuring Euclidean distances on a flat surface underestimated the distance traveled, relative to the reference. The second approach, which calculated the distances constrained to a road network, also varied substantially from the reference, underestimating it in some areas and overestimating in others. Finally, the third approach, which accounted for land cover and elevation but ignored the directionality of slopes slightly underestimated travel times (Wood et al. 2018).

Lundberg (2012) examined the local cycling and walking networks through Geographic Information Systems (GIS) using accessibility. They extracted a percent slope raster layer from DEM layer that was obtained from part of the National Elevation Dataset (NED). the percent slope of the DEM ranged from 0 to 360. In Arc Map, when the slope angle equals 45 degrees, the rise is equal to the run. Expressed as a percentage, the slope of this angle is 100%. As the slope angle approaches vertical (90o), the percentage slope approaches infinity. An X,Y coordinate was first calculated for the start point of each line segment. Next an X,Y coordinate was calculated for the end point of each line segment. Arc Map’s 3D Analyst extension was used to convert the street network into a 3D layer, at which point percent slope could then be calculated as the Z-value for each of the line segments in the network. A Z-value (elevation) was calculated at the start points and end points of each line segment. The following equation was used to derive percent slope for each line segment:

slope values indicate uphill travel while negative slope values indicate downhill travel. In this regard, they proposed different walking and cycling speeds based on the different slopes using Parkin and Rotheram (2010) findings on the impact of slope on bicycle travel speeds(Parkin and Rotheram 2010).Table 5. summarizes the various bicycle travel speeds used in the GIS modeling.

**Table 7.** Bicycle travel speeds used in GIS modeling

| **Slope** | **Speed(mph)** |
| --- | --- |
| -10 | 18.8 |
| -7 | 17.1 |
| -5 | 16.1 |
| -2 | 14.5 |
| 0 | 13.4 |
| 2 | 11.7 |
| 5 | 8.9 |
| 7 | 7.2 |
| 10 | 4.5 |

Pedestrian travel speeds were also calculated based on the effect of slope. Tobler’s hiking function was used to identify the effect of slope on travel speed. The following equation represents the modified Tobler’s formula adjusted for percent slope:

Where v is velocity, e is the base for natural logarithms, and s is the slope in percent. Table 6. summarizes a pedestrian’s travel speed used in the modeling in GIS.

**Table 8.** Pedestrian travel speeds used in GIS modeling

| **Slope** | **Speed(mph)** |
| --- | --- |
| 10 | 1.6 |
| 7.5 | 2.1 |
| 5 | 2.4 |
| 2.5 | 2.8 |
| 0 | 3.1 |
| -2.5 | 3.6 |
| -5 | 3.1 |
| -7.5 | 2.6 |
| -10 | 2.3 |

In another study, Paez et al (2020) calculated the slope from the vertical and horizontal displacements. The instantaneous slope (m) is given by the derivative of with respect to x. this is given by the following expression (Páez et al. 2020):

In a DEM layer, two physical aspects of the landscape that relate to resistance can be obtained directly from the grid, namely the vertical displacement and the horizontal displacement between nodes i and j. and $h $ are vertical and/or horizontal displacements respectively. This slope is linked to speed via Tobler’s formula for hiking travel (Tobler 1993):

where the speed s is in m/min. The amount of speed can be converted into travel time in minutes if it is divided the distance by speed as follows:

where can be the distance on the surface as discussed above or can be approximated by the horizontal distance . As seen in Fig. 2, travel time tends to increase as the slope in creases.

|  |
| --- |
| Figure 2: Relationship between surface distance/travel time and slope |

**Weather**

Other factors that are associated with the natural environment and have also been shown to affect cycling and walking trips are as follows: weather, temperature, shade, and aesthetics. The type of weather an individual has to travel through has been identified as a principal factor in the decision process for employing non-motorized travel modes. The pinnacle conditions that individuals consider using non-motorized travel include dry weather and pleasant temperatures (60 to 75) (Zacharias 2001). High amounts of shade cover over a network and available aesthetics along a route increase the rates for non-motorized travel (Zahran et al. 2008).

**Level of Traffic Stress**

Several of the cycling accessibility approaches incorporate bicycle infrastructure using level of traffic stress (LTS) (Imani, Miller, and Saxe 2019; Murphy and Owen 2019). The LTS method was first proposed by Furth, Mekuria et al. (2016) to categorize street segments into 4 categories based on the number of lanes, presence of a parking lane, the speed limit, the bike lane and parking lane width, and any bike lane blockage (Furth, Mekuria, and Nixon 2016).Faghih Imani et al. (2019) and Murphy and Owen (2019) compare cycling accessibility measures using different LTS categorizes to calculate service areas. Both studies exclude highways and high-volume roads from the network and classify into LTS categories using attribute information available from the network dataset and used the City of Toronto open data and OSM data respectively(Imani, Miller, and Saxe 2019; Murphy and Owen 2019).

The Canadian Bikeway Comfort and Safety (Can-BICS) Classification System aims to provide a common nomenclature for bicycle facilities based on user safety and comfort. The Can-BICS classification designates bicycling facilities into three categories: high, medium, and low comfort infrastructure. There is some general alignment between Can-BICS categories and LTS criteria, however, there are a few main differences:

Local street bikeways are classified as high comfort using Can-BICS, but either LTS 1 or 2 depending on the number of lanes.

Painted bike lanes may be assigned LTS 1 to 4 depending on the speed, width, and presence of parking lanes, whereas in Can-BICS, painted lanes are low comfort facilities.

Trails and walkways in parks are LTS 1 but may be categorized as non-conforming Can-BICS facilities depending on the trail surface (e.g., gravel or dirt vs. paved).

**Table 9.** The Canadian Bikeway Comfort and Safety (Can-BICS) Classification System

| **Facility Type** | **Can-BICS Class** | **LTS Category** |
| --- | --- | --- |
| Cycle tracks | High comfort | 1 |
| Local street bikeway | High comfort | 1 or 2 |
| Bike paths | High comfort | 1 |
| Multi-use paths | Medium comfort | 1 |
| Painted Bike lanes | Low comfort | 1 to 4 |
| Park trails and walkways | Non-conforming | 1 |

**Origins/destinations & applying weights**

Typically, the way in which opportunities are measured depends on the type of opportunity and whether one or multiple opportunity types are considered. For example, the studies measuring job accessibility or number of people served by transit consider a total count, whereas for urban park access, Reyes et al. (2014) and Cheng et al. (2019) consider cell counts to account for park area(Reyes, Páez, and Morency 2014; Cheng et al. 2019). Among walkability and bikeability indices it is also common to apply weights to the variables depending on the goals for analysis (L. D. Frank et al. 2010; D. S. Vale, Saraiva, and Pereira 2016; Arellana et al. 2021).

The majority of studies focus on origin-based accessibility (access to destinations), however, as argued by Vale et al. (2015), accessibility at destinations is also important. For example, individuals may reside in high accessible areas, but work in low-accessibility areas. In this respect, topology-based measures, may be preferred, or it may be useful to consider accessibility in terms of the population served around destinations of interest(D. S. Vale, Saraiva, and Pereira 2016).

## Conclusion

Overall, there remains considerable variation in the types of accessibility measures applied in the context of walking and cycling. Among the four main types of active accessibility measures identified, the majority of recent studies use an activity-based approach, either measuring cumulative opportunities (within a catchment area / weighted by distance from the origin) or measuring gravity models. The activity-based approaches mainly vary in terms of the travel time and distance thresholds, and weighting impedance functions considered.

Many of the walking approaches, for instance, aim to incorporate a variable walking threshold (depending on age or location), while this is not seen within the context of cycling – where a prioritization of measures by route infrastructure is more apparent. Conversely, attention to infrastructure type, or comfort and safety, is not seen among pedestrian-focused studies.

When selecting an accessibility measure, there is evidently a trade-off between complexity and measure interpretability. While adding more complexity or multiple indices for different population groups, may increase accuracy, a simple, and easy to implement measure may be more important for widespread use.

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