A Historical Analysis of the Evolution of Active Travel Behaviour in Canada

Alice Anonymous[a,1,*], Bob Security[b], Cat Memes[b,2], Derek Zoolander[a,2]

[a] *Big Wig University, 1 main street, Gotham, 123456, State, United States*
[b] *Department, A street 29, Manchester,, 2054 NX, The Netherlands*

Abstract

This is the abstract.

It consists of two paragraphs.

Keywords: keyword1, keyword2

1. Introduction

The idea that travel behaviour can be influenced by the city form has attracted growing interest urban and transportation planning. Cities intend to encourage their residents to adopt more sustainable modes of transportation, including walking, cycling, and public transit, by developing an environment with a variety of transportation alternatives and, at the same time, increasing accessibility - understood as the ease of reaching destinations and opportunities (Iacono, Krizek, and El-Geneidy 2008). Because of their significant role in enhancing and promoting urban sustainability (Hino et al. 2014; Lamiquiz and Lopez-Dominguez 2015), active transportation modes, such as walking and cycling, are playing a central role in urban mobility research and policy-making (S. Handy 1993; Clifton and Handy 2001; Frank and Engelke 2001; Krizek 2005; Sallis et al. 2004; Vandenbulcke, Steenberghen, and Thomas 2009; Wu et al. 2019). Walking and cycling accessibility are closely related, contributing together to the concept of "active accessibility" or "non-motorized accessibility", and, when considered in the urban and transportation planning process, reducing dependence on private vehicles and promoting healthier and more sustainable travel behaviour among residents.

There are two main components when measuring accessibility: (1) the location and power of attraction of urban opportunities (trip benefit) and (2) the barrier in travel from the origin in the network to the destination (trip cost). A way for measuring the cost of travel when calculating accessibility is using impedance functions, a methods that is receiving attention from transportation planning scholars, urban geography, and sustainable development (Frank et al. 2005; Krizek 2005; Currie 2010; Iacono, Krizek, and El-Geneidy 2010; Yang and Diez-Roux 2012; Millward, Spinney, and Scott 2013; Nassir et al. 2016; Saghapour, Moridpour, and Thompson 2017; Wu et al. 2019). The impedance functions have different forms and all of them serve as a tool to understand the travel behaviour and as measure of the willingness to travel a certain distance to achieve a desired destination, where a service or an opportunity is located (Taylor 1975; Fotheringham 1981; Kwan 1998; Eldridge and Jones III 1991; Luoma, Mikkonen, and Palomaki 1993; Papa and Coppola 2012; Yang and Diez-Roux 2012; Millward, Spinney, and Scott 2013; Vale and Pereira 2017). In this concept, areas with higher accessibility are those characterized by a lower impedance when traveling to desirable destinations. When talking about active accessibility, increasing the distance between

* Corresponding author

Email addresses: alice@example.com (Alice Anonymous), bob@example.com (Bob Security), cat@example.com (Cat Memes), derek@example.com (Derek Zoolander)

[1] This is the first author footnote.

[2] Another author footnote.

two points generally implies in a decreasing in the probability of that trip being done by walking or biking (Hansen 1959; Pirie 1979; S. L. Handy and Niemeier 1997; K. T. Geurs and Ritsema van Eck 2001; Bhat et al. 2002; Church and Marston 2003; Kwan et al. 2003; K. T. Geurs and Van Wee 2004; Levinson and Krizek 2005; Cascetta, Carteni, and Montanino 2013). However, more information about the willingness of some individuals to walk or cycle greater distance is needed, as well as more data on how distance affects the type and feasibility of the activity, destinations desirability, and the characteristics of those embarking on the trip in different contexts. In this context, investigate the evolution and dynamics of impedance function over time becomes important, since they're easily impacted by changes in the transportation network or in urban spatial configurations (Iacono, Krizek, and El-Geneidy 2008; Iacono, Krizek, and El-Geneidy 2010). Luoma, Mikkonen, and Palomaki (1993) evidenced a decreasing in the distance decay parameter over time, attributing this trend to improvements and maturation of the transportation system (Luoma, Mikkonen, and Palomaki 1993), and Mikkonen and Luoma (1999) argues that this difference was mainly caused by the establishment of new big retail store units, elucidating the factors behind these temporal patterns in the gravity models patterns (Mikkonen and Luoma 1999).

Since the beginning applications of the gravity-accessibility models, a range of impedance functions have been applied to describe the distribution of walking and cycling trips, wether for general or specific purposes (Iacono, Krizek, and El-Geneidy 2008; Iacono, Krizek, and El-Geneidy 2010; Larsen, El-Geneidy, and Yasmin 2010; Yang and Diez-Roux 2012; Millward, Spinney, and Scott 2013; Vale and Pereira 2017; Li, Huang, and Axhausen 2020).

Selecting an appropriate impedance function can be challenging and results in a diverse range of cost decay functions that are employed as impedance functions in accessibility measures, including **threshold functions** (e.g., binary Step Function and multiple Step Function) and **smooth cost decay functions** (e.g., log-normal, normal, gamma, and exponential function) (De Vries, Nijkamp, and Rietveld 2009; Reggiani, Bucci, and Russo 2011; Osth, Lyhagen, and Reggiani 2016; ITF. 2017). The variety of functions relies in how scholars approach the influence of distance, with negative exponential distance-decay functions are commonly used in assessing non-motorized accessibility, capturing the willingness of individuals to walk or cycle to destinations (S. L. Handy and Niemeier 1997; K. T. Geurs and Ritsema van Eck 2001; Iacono, Krizek, and El-Geneidy 2010; Vega 2012; Millward, Spinney, and Scott 2013; Vale and Pereira 2017; Li, Huang, and Axhausen 2020).

The merit of this function is due to its ability to assign decreasing influences to more remote opportunities, giving a more accurate estimate for shorter trips (Iacono, Krizek, and El-Geneidy 2010; Kanafani 1983; Fotheringham and O'Kelly 1989). However, in addition to determine the form of the impedance function, scholars also need to specify the variable used to measure impedance, which can be either time, distance, monetary cost, a combination these last variables or even a generalized cost concept. Among these options, the choice between time and distance as the impedance has been found to be most used based on previous studies (Iacono, Krizek, and El-Geneidy 2010; Hull, Silva, and Bertolini 2012; Sun, Lin, and Li 2012; Lowry et al. 2012; Vasconcelos and Farias 2012), with distance being more adopted in non-motorized applications since extracting accurate travel times from existing network models is challenging (S. L. Handy and Niemeier 1997; Iacono, Krizek, and El-Geneidy 2010; Yang and Diez-Roux 2012; Arranz-Lopez et al. 2019). Additionally, estimate impedance function to active transportation modes requires appropriate travel survey data that is able to capture pedestrian and cycle behaviour, resulting in researchers recurring to retrospective questionnaires to assess subjective aspects such as the frequency and duration of walking and cycling activities. Notably, regional household travel surveys that include trips made by non-motorized modes have been employed for this purpose (Iacono, Krizek, and El-Geneidy 2010; Millward, Spinney, and Scott 2013). In opposition to these specific surveys, some data sets provides a nationwide perspective, including travel for different purposes and detailing the trip with valuable information, named episodes, regarding the origins, destinations, and time-based lengths. Besides this type of data can provides a deeper comprehension about the active transportation behaviour, only few studies have examined travel behaviour nationally.

Aiming to address the mentioned challenges, this study has as the main goal identifying appropriate impedance functions for active transportation modes for various destinations and time periods in Canada. Additionally, the present paper realizes a comparative analysis of travel behaviors associated with these two modes. To do achieve this objective, we utilize the {ActiveCA} R package. {ActiveCA} is an open data product in the form of an R data package with information about active travel in Canada. This data product is based on Public Use Microdata Files of Statistics Canada's General Social Survey (GSS) program with a focus on the Time Use Survey cycles. To build this package, Santos and Paez [*include the reference*] extracted all walking and cycling episodes and their corresponding episode weights for GSS cycles, Cycles 2 (1986), 7 (1992), 12 (1998), 19 (2005), 24 (2010), and 29 (2015), spanning a period of almost thirty years. Origins and destinations were categorized, enabling the investigation of active travel for broad destination categories and purposes.

We recognize that non-work travel encompasses a range of trip purposes and diverse traveler behaviors, which makes impedance functions essential analytical tools for studying non-work accessibility. Grengs (2015) emphasizes the importance of elaborating distinct functions for each travel purpose, a principle that guides this analysis (Grengs 2015). Our investigation covers a variety of trip goals, ranging from commutes to homes, workplaces, or educational institutions to social visits, outdoor activities, business trips, shopping, cultural outings to libraries, museums, or theaters, dining out, and engaging in religious practices. Our research aims to enhance the current knowledge about active travel behaviour and provide empirical data about frequency and duration of typical pedestrian and cycling trips for different purposes, by applying the methodology on a nationally representative samples of Canadian residents. Lastly, this comprehensive analysis seeks to contribute to the ongoing conversation on active transportation, highlighting its role in influencing transportation plans to a more sustainable alternative.

2. Background

Accessibility is understood as the potential to access spatially distributed opportunities, taking into account the challenges associated with this access (Paez, Scott, and Morency 2012). Usually, the effect of travel costs is expressed by "impedance functions" or "distance decay functions" (Hansen 1959; Koenig 1980; Fotheringham 1981). In general, they are derived from estimates based on distributions of sample data that reflect variations in the willingness of individuals to travel different distances to reach opportunities (Hsiao et al. 1997; Zhao et al. 2003; Iacono, Krizek, and El-Geneidy 2010; Li, Huang, and Axhausen 2020). The main objective of the impedance function is to describe the decrease in the intensity of interaction as the cost of travel between locations increases and, in general, the cost of travel is measured in terms of the distance between the places of origin and destination or in terms of the time spent reaching the destination from the point of origin. In general, these functions describe how an increase in the associated distance/travel time inversely affects the potential for making the trip; in essence, distant facilities are less likely to be used compared to closer ones (Hansen 1959; Koenig 1980; Fotheringham 1981; Skov-Petersen 2001). Thus, the "distance decay" effect suggests that adding a unit of distance to a long trip is less significant than adding a unit to a shorter trip (Carrothers 1956), since the farther location already has a lower probability of access for the person willing to travel Carrothers (1956). Examining the impedance functions related to different modes of transport and destinations is a good way to understand the travel behavior attributed to each mode. When segmenting modal trips by destinations, it is possible to compare the distribution of trips between multiple finalities for each mode of transport (work-related and non-work-related) and examine any allegations about travel behavior. For example, current interest in creating "livable" communities revolves around vague assumptions about individuals' willingness to walk or bike to different destinations, such as the assumption that people are generally willing to walk up to a quarter mile to access most places (Untermann 1984). However, there is still little information on whether certain individuals are willing to walk or cycle longer distances and, if so, how far they are willing to go. In addition, more evidence is needed on the influence of trip characteristics, destination attractiveness and individual characteristics on the impact of distance on walking and cycling behavior (K. Geurs 2006).

2.1. Impedance functions in accessibility measures

Since Hansen's (1959) research, different categories of accessibility measures have been developed, such as indicators based on actives, infrastructure, individuals and utilities (Hansen 1959; K. T. Geurs and Van

Wee 2004). The family of gravity-based accessibility have been widely used in active modes (Miller 2005). Many gravity-based accessibility measures derive from the work of Hansen (1959), represented in (Equation 1), in which an impedance function weights opportunities:

$$A_i = \sum_{j=1}^{J} O_j . f(c_{ij}) \tag{1}$$

The accessibility score A_i at each origin i is obtained by summing up the opportunities O available at destination j, where i and j are sets of spatial units in a region. However, the number of opportunities in each destination is gradually discounted as travel costs become higher and the the rate at which this weight decreases is determined by a decay function. $f(c_{ij})$ represents the impedance during the trip from origin i to destination j and c_{ij} reflects the generalized travel cost, potentially encompassing factors such as time, distance and effort. In this way, the impedance function $f(c_{ij})$ allows the accessibility analyst to define a measure of travel behavior with precision: the relationship between the "population" at an origin and where they normally want to or can go to reach "opportunities" at destinations. The definition of the impedance function $f(c_{ij})$ is very important from this perspective.

Another type of family of accessibility measures are *cumulative opportunity* metrics, commonly referred to as isochronous indices. The binary function Equation (2) forms the basis of the cumulative opportunities maeasure approach. This function determine accessibility by summing up the number of opportunities available within a specific limiar of travel time or distance from a reference point, without discounting the potential of the trip in relation to the associated cost. They use a rectangular function, categorizing the trip as "acceptable" within certain limits and "unacceptable" beyond them. One of the main complexities of these metrics is deciding what the appropriate limiar point is. This decision may be based on the prevailing mobility patterns of the population or may reflect established norms, conventions or informed projections of the researcher (Vickerman 1974). Note that the cumulative opportunity measure can be understood as a special case of a gravity-based measure in which the weight of each opportunity is defined by a binary function, rather than a gradually decaying function.

$$C_{ij} = \begin{cases} 1 & \text{if } c_{ij} \leq x \\ 0 & otherwise \end{cases} \tag{2}$$

Among the various mathematical forms that can represent impedance functions, the negative exponential function is the dominant choice in accessibility research (Meyer and Miller 1984; Gutierrez, Gonzalez, and Gomez 1996; Kwan 1998; Apparicio et al. 2008; Iacono, Krizek, and El-Geneidy 2008; Iacono, Krizek, and El-Geneidy 2010; Larsen, El-Geneidy, and Yasmin 2010; Millward, Spinney, and Scott 2013). Its high adoption can be attributed mainly to its ability to give greater weight to nearby opportunities, and greater weight to distant opportunities - a highly relevant characteristic for active modes of transportation, such as walking and cycling. Song (1996) noted in his examination of alternative measures of accessibility that the negative exponential form ($e^{-\beta x}$) stands out as the most suitable for explaining population distribution due to its gradual decline, which aligns with empirical data and accurately captures the influence of proximity on accessibility (Song 1996). Kanafani (1983), who highlighted the suitability of this function for modeling non-motorized modes, emphasizing its ability to better estimate shorter trips compared to the power function. In addition to Song and Kanafani, several other studies (Kanafani 1983; Fotheringham and O'Kelly 1989; De Vries, Nijkamp, and Rietveld 2009; Iacono, Krizek, and El-Geneidy 2010; Signorino et al. 2011; Prins et al. 2014) use the negative exponential function after comparison with empirical trip distribution data.

Researchers can adopt other forms of impedance functions when calculating the distance decay effect in accessibility analysis. One of these options is to adopt a probability density function (PDF) [SOUKOV]. Using a PDF, $f()$ can be interpreted as the probability density of a trip occurring for each value of travel cost c_{ij}. If a graph of the PDF (y-axis) is plotted against the travel cost c_{ij} (x-axis), the probability of a trip occurring between a given range of c_{ij} is the area under the curve. In this case, the total area under the PDF curve always sums to 1, meaning that there is 100% probability that the trip will occur between the minimum and maximum c_{ij}.

Dunn et al. (2023) presented a set of distributions that serve as PDFs. From their survey, we selected some options for $f()$ commonly used in accessibility research and their impact on the number of opportunities (the sum of opportunities) at specific travel costs c_{ij}, namely: uniform, negative exponential, gamma, normal, and lognormal distributions.

- **Uniform distribution**

The uniform distribution or rectangular PDF looks very similar to the binary function, since it only returns one of two values, but ensure that area under the curve for the range of c_{ij} is 1. The uniform distribution PDF is shown in (Equation 3).

$$f(c_{ij})^{uniform} = \begin{cases} \frac{1}{c_{max} - c_{min}} & \text{for } c_{min} \leq c_{ij} \leq c_{max} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

The parameters to be calculated are c_{max} and c_{min}, which represent the maximum and minimum travel costs that describe the observed or assumed willingness to reach destinations. In this distribution, all values within the interval are equally likely, and all values outside the interval have probability 0, assuming that the population's potential to interact with these opportunities is zero.

- **Exponential distribution**

The exponential distribution PDF equation is given by Equation (4). This model suggests that impedance decreases exponentially with increasing cost (c_{ij}). The parameter β represents the decay rate, with higher values indicating a faster decrease in accessibility with increasing cost. As already mentioned, this function is widely used due to its simplicity and ability to model the rapid drop-off in accessibility over distance.

$$f(c_{ij}) = e^{-\beta c_{ij}} \text{ with } c_{ij} \geq 0 \tag{4}$$

- **Gamma distribution**

The exponential distribution PDF equation is presented by the Equation 5.

$$f(c_{ij}) = \begin{cases} \frac{1}{\sigma^{\alpha}\Gamma(\alpha)} c_{ij}^{\alpha-1} e^{\frac{-c_{ij}}{\sigma}} & \text{if } 0 \leq c_{ij} < \infty \text{ and } \alpha, \sigma > 0 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

Where $\Gamma(\alpha)$ is the gamma function to be estimated. In this case, the probability is typically low at low cost, higher at medium cost, and low again at high cost. The higher the σ (scale rate) parameter, the higher the probability that the majority of trips will be in the low cost range. So at low values of the σ (scale rate) parameter, the same probability is spread over a wider range of travel costs. For the α (shape) parameter, the higher the value, the higher the probability density of trips with a higher average cost [SOUKHOV].

- **Lognormal distribution**

The normal distribution, also often called the Gaussian distribution, is suitable when the travel cost is found to be distributed normally. The normal distribution has the PDF form displayed in Equation (6).

$$f(c_{ij}) = \frac{1}{\sqrt{2\pi}\sigma c_{ij}} e^{-\frac{(\ln c_{ij} - \mu)^2}{2\sigma^2}} \tag{6}$$

In this equation, μ and σ are the mean and standard deviation of the logarithm and need to be estimated together to control the shape of the normal curve. In this distribution, about 68% of the observations will fall within 1 standard deviation of the mean, about 95% will fall within 2 standard deviations, and about 99.7% will fall within 3 standard deviations of the mean. In this case, the values close to the mean will have the highest probability.

- **Lognormal distribution**

In many cases, the logarithm of the travel cost is found to be distributed normally. The lognormal distribution has the PDF form displayed in Equation (7).

$$f(c_{ij}) = \frac{1}{\sqrt{2\pi}\sigma c_{ij}} e^{-\frac{(\ln c_{ij} - \mu)^2}{2\sigma^2}} \tag{7}$$

It this equation, μ and σ are the mean and standard deviation of the logarithm, and need to be estimated for together control the shape of the log-normal curve. Similar to the gamma function, the probability is typically low at low cost, higher at medium cost, and low again at high cost.

As the complexity of the PDF increases, so does the flexibility to explain travel behaviour. However, the estimation of the impedance function parameters needs to be calibrated if the accessibility estimates are to be representative of people's travel behaviour. This requires additional travel behaviour data to be used in the calibration process. In our case, we will use the ActiveCA package to obtain the impedance functions, as the package contains ready-to-use data from GSS cycles.

2.2. The GSS survey

The GSS provides a comprehensive cross-sectional snapshot of the Canadian population through telephone surveys established in 1985. The survey coverage area includes both metropolitan and non-metropolitan regions, ensuring a diverse and representative sample of the Canadian population. Specifically, the ten provinces of Canada were divided into distinct geographic strata for sampling purposes. Many Census Metropolitan Areas (CMAs), such as St. John's, Halifax, Saint John, Montreal, Quebec City, Toronto, Ottawa, Hamilton, Winnipeg, Regina, Saskatoon, Calgary, Edmonton, and Vancouver, were treated as separate strata. Additional strata were formed by grouping other CMAs within Quebec, Ontario, and British Columbia, and by categorizing non-CMA areas within each province into their own strata.

These surveys encompass an array of socio-demographic inquiries combined with questions concentrating on specific core themes, such as health, time use, and aspects like social support and aging (Statistics Canada, 2015). One of the standout features of the GSS is its recurring "time use" cycle, which concentrates in the daily activities of Canadians. This cycle captures the amount of time individuals allocate to various tasks and the sequence, location, and concurrent activities, offering a wide view of Canadians' daily lives. The questions within this cycle have been adapted and refined over the years to reflect the changing dynamics of daily life, ensuring that the data remains pertinent and contemporary.

In order to investigate the historical active travel behavior in Canada, Six GSS cycles were thoroughly considered for this study: Cycles 2 (1986), 7 (1992), 12 (1998), 19 (2005), 24 (2010), and 29 (2015). The 1986 cycle is notable because it was the first national random sample examining Canadian time-use patterns. Data filtering was essential given the research focus on travel behavior, particularly walking and cycling. It required an exhaustive extraction of entries relevant to these two travel modes. Each GSS Cycle is derived from two microdata sources: the Main and Episode files. The Main file comprises questionnaire responses and associated data from participants, while the Episode files furnish detailed insights into every activity episode reported by the respondents. For this study, we employed the episode files to establish a comprehensive dataset for impedance function analysis. This dataset encompasses variables such as individual ID, start time, end time, time duration, origins and destinations of each walking and cycling trip, and weight. It should be noted that each record represents a single activity in a respondent's day, ensuring that all episodes collectively span twenty-four hours (or 1440 minutes). The weight parameter signifies the number of time-use episodes that a particular record in the Episode File represents.

3. Materials and Methods

We can summarize the methodology in three main steps. The first step preprocess the chosen GSS survey cycles, based on Public Use Microdata Files of Statistics Canada's GSS program. The second step evolves calibrating the best impedance function for every combination of cycle, destination, and active travel mode. The third stage involves evaluating the impedance functions, comparing their temporal evolution.

To facilitate collaboration and further analysis, we created the ActiveCA R data package, an Open Data Product that provides analysis-ready data from Cycles 2 (1986), 7 (1992), 12 (1998), 19 (2005), 24 (2010), and 29 (2015) of the GSS regarding active travel. The Rmarkdown code needed to obtain these outputs from the raw data files is available through a Zenodo repository linked to our GitHub page, in line with the best practices of spatial data science. These contributions improve our understanding of active travel behaviour in Canada and provide a basis for future research and policy-making.

3.1. Preprocessing the GSS surveys

For each selected cycle of the GSS surveys, we reviewed the episode files to identify cases with activities listed as walking or cycling, selecting the locations immediately before and after the mobility episode. Doing this, we were able to identify the origin and the destination of the active travel episode. We labeled the code variables with their appropriate descriptions, identifying the transportation mode, activity/reason of the travel, as well the province and urban classification of the respondent's residency (if the respondent lives in a Census Metropolitan Area or in a Census Agglomerations).

Additionally, it was necessary to guarantee the data consistency across the surveys, since they have employed a variety of variable coding schemes. The range of activities and destinations considered in the surveys changed from 1986 to 2015. In the first survey (in 1986), there were only three options of origin/destination location available to the respondent: their home, other's home and work or studt. In its turn, the most recent survey (2015) counts with more than 10 possible destination, including sport centre, restaurant, health clinics and more. In order to achieve uniformity, the activity categories from 2005, 2010, and 2015 were synchronised, and a similar process was employed for those from 1986, 1992, and 1998. For the preceding years (1986, 1992, and 1998), the trip origins and destinations were classified as "Home," "Other's home," and "Work or School." In the subsequent years (2005, 2010, and 2015), these categories were expanded to include "Business," "Restaurant, bar or club," "Place of worship," "Grocery store, other stores or mall," "In the neighbourhood," "Outdoors," "Library, museum or theatre," and "Sport centre, field or arena". It is also important to note that the 1986 dataset exclusively contains data on walking trips, with no records of cycling trips for that year.

Para avaliar a significancia estatistica de possiveis diferencas temporais entre as funcoes de impedancia de cada destino, we employed the Kruskal-Wallis test to determine whether the PDF medians differed among the year for every destination. We selected the Kruskal-Wallis test because this test do not assume that a normal distribution for the functions, which is important because we are still trying to determine the type of PDF for every destination, transport mode and year. If a median difference was identified between the groups, we then applied the pairwise Wilcoxon test to discern which specific group differed from the others. We adopted a significance level of 0.05 for both tests.

3.2. Estimating impedance function parameters

The objective of this research was to compute the appropriate impedance functions for each destination, mode of transportation and survey year. We applied the "fitdistrplus" package to calculate the best PDF for every destination, mode of transportation and survey year, between the options: uniform, negative exponential, gamma, normal, and lognormal distributions.

In order to calculate the impedance functions, two filters were applied in the GSS data set. The first is that we excluded all trips with travel times higher than 100 minutes (1.5 hours). An exploratory data analysis showed that, taking into account all the walking and cycling episodes (12113 in total), less than 0% of the episodes have a trip duration higher than this limit. It was also possible to know that trips with a duration higher than 100 minutes are mainly composed of hiking and camping episodes. The second filter was realized to select only the population living in a larger urban population centre (a Census Metropolitan Area (CMA) or Census Agglomeration (CA)). We decided to apply this restriction because the travel behaviour of residents of CMA and CA areas tends to be very different from those outside these large urban centres in terms of active travel.

After calculate the impedance functions, we conducted an initial statistical test evaluate if the temporal differences in for destination was statitical significant throught the years. # Results and discusion

3.3. Descriptive analysis of walking and cycling trips from 1992 to 2015

After applying the filters to the GSS surveys, we obtained a total of 1.2113×10^4. Table 1 contains the number of episodes about walking and cycling trips between 1992 and 2015, obtained from the GSS cycles. The year 2005 is the year with the most episodes, 4471, representing approximately 37% of all active travel episodes. The year 2005 is followed by 2010, with 3543 episodes (representing 29% of the total), then 2015 (2899 episodes, 24% of the total), 1998 643 episodes, 5% of the total), and 1992, with only 557 episodes, representing 5% of the total.

When analyzing the two active transportation modes, walking episodes account for 93%, while the remaining 7% are cycling episodes. However, it is worth mentioning that, while in 2015 cycling episodes represented only 7% of the active travel episodes for that year, in 1992 the cycling episodes represented 12% - the highest share of this mode across all years. In the next survey (1998), it drops to around 9%, stabilizing at around 7% thereafter.

Table 1: Number of episodes identified in each active transportation mode by year

	Year					
Mode	1992	1998	2005	2010	2015	Total
Cycling	67	56	289	209	214	835
Walking	490	587	4182	3334	2685	11278
Total	557	643	4471	3543	2899	12113

Tables 2 presents statistic on travel time, which is used as the travel cost to calculate the impedance functions, by active transportation mode. The maximum time spent on walking trips varied between 90 and 100 minutes across the years. It is important to remember that trips with duration greater than 100 minutes were excluded from the analysis. The mean walking time also varies, starting at 21 minutes in 1986, dropping to 12 minutes between 1992 and 2010, and increasing again to 16 minutes in 2015. However, it is known that the mean is a statistic that is highly influenced by extreme values. For this reason, we analyze the median travel time, as it is more representative of the typical travel time. The median time spent walking is 15 minutes in 1992, then drops to 5 minutes in 1998 and remains constant at 10 minutes from 2005 to 2015.

However, the analysis of travel time statistics alone does not fully explain the reasons behind these fluctuations in travel time over the years. We can affirm, however, that there was a reduction in the time spent walking during the analyzed period, with a one-third reduction in the median walking travel time since 1992.

For cycling trips, the maximum travel time varies from 90 to 100 minutes, similar to walking, except in 1998 when the maximum travel time recorded was 80 minutes. The average cycling travel time is more constant, ranging from 19 minutes in 2005 to 25 minutes in 1992 and 1998. Again, when we analyze the median travel time, we see that the typical cycling travel time dropped from 20 minutes in 1992 to 15 minutes in 2005, 2010, and 2015, possibly reflecting advancements in bicycle technology or changes in cyclists' behaviors.

As highlighted in Figure 1, over the 30 years studied, the typical duration of walking trips was consistently lower than that of cycling trips. As already mentioned, both medians decayed when compared to 1992, and various factors might have precipitated this trend, such as urban sprawl, increased reliance on motorized transport, or societal preferences for faster modes of transportation.

Table 2: Descriptive statistics for episodes with active transport records

		Year				
Mode	Statistic	1992	1998	2005	2010	2015
Walking	count	490	587	4182	3334	2685
	max	90	100	100	90	95
	mean	21	12	12	12	16
	median	15	5	10	10	10
	min	5	1	1	1	5
Cycling	count	67	56	289	209	214
	max	90	80	95	100	90
	mean	25	25	19	20	23
	median	20	18	15	15	15
	min	5	2	1	2	5

Figure 1 shows the percentage of each destination by year and by mode of transport. For all the years analyzed, 'Home' is the most common travel destination, regardless of whether the mode of transport considered is walking or cycling, with levels above 42%. After that, 'Work or school' appears as the second most common destination, especially for journeys by bicycle, with a peak of almost 34% of trips by bicycle in 1998, a high drop to 22% in 2005, rising again to levels close to 30% in 2015. Along with the two destinations already mentioned, 'Other's home' is the only other destination present in the GSS surveys since 1992. This last destination seems to be a destination with a higher share when it comes to walking trips, but for both modes of transportation it seems that respondents are going less and less to other people's homes - a fact that can be explained by new communication technologies, in which a person doesn't need to visit another person's home to keep in touch with them.

After 2005, the expansion of the destination highlights some new popular locations. For example, 'Grocery store' appears as the third most chosen destination, varying from 10% in 2005 to 6.5% in 2015 for cycling trips and from 13.3% to 12.6% for walking trips. When considering walking trips, 'Restaurants' appears as another well chosen destination and, in the case of cycling trips, 'Outdoors' appears as a well chosen destination.

Figure 2 present the box plot graphs showing the travel time distribution for active transportation modes over the years, categorized by destination. Some destinations are presented in only one survey, such as 'Sport area', 'Neighbourhood,' and 'Business'. These new destination exhibit typical walking travel times 10 minutes. For cycling trips, 'Business' recorded no trips, while 'Sport area' and 'Neighbourhood' registered typical travel times of 30 and 15 minutes, respectively.

For destinations included in more than one survey, we can compare the temporal evolution of travel times. Starting with the walking trips, we can note that there is a tendency of increasing travel times for 'Restaurants' and 'Outdoors' (both increasing from 5 in 2005 to 10 minutes in 2015) and 'Place of worship' (rising from 10 in 2005 to 15 minutes in 2015). In contrast, some destinations presented a decline in travel times, where the case of 'Cultural venues,' which had a median travel time of 2005 and drop to 5 minutes in 2015, and 'Home' which start the time series with a minutes in 1992 and dropped to 10 minutes by 2015. Other destinations maintained an almost constant travel time. In general, while 'Place of worship' displayed the maximum median travel time of 15 minutes, the general median walking time cuttoff appears to be 10 minutes, with most of trips occurring below this limit.

For cycling trips, an increasing trend in travel times is evident for destinations such the destinations 'Grocery store' (rising from 10 to 15 minutes between 2005 and 2015), 'Outdoors' (increasing from 15 in 2005 to 20 minutes in 2015), and 'Home' (retuning to the 1992 typical travel time of 20 minutes after dropping to 10 minutes in 2010). However, travel times decreased for destinations like 'Other's home' and 'Place of worship', where the typical cycling travel time declined from 20 minutes in their first recorded

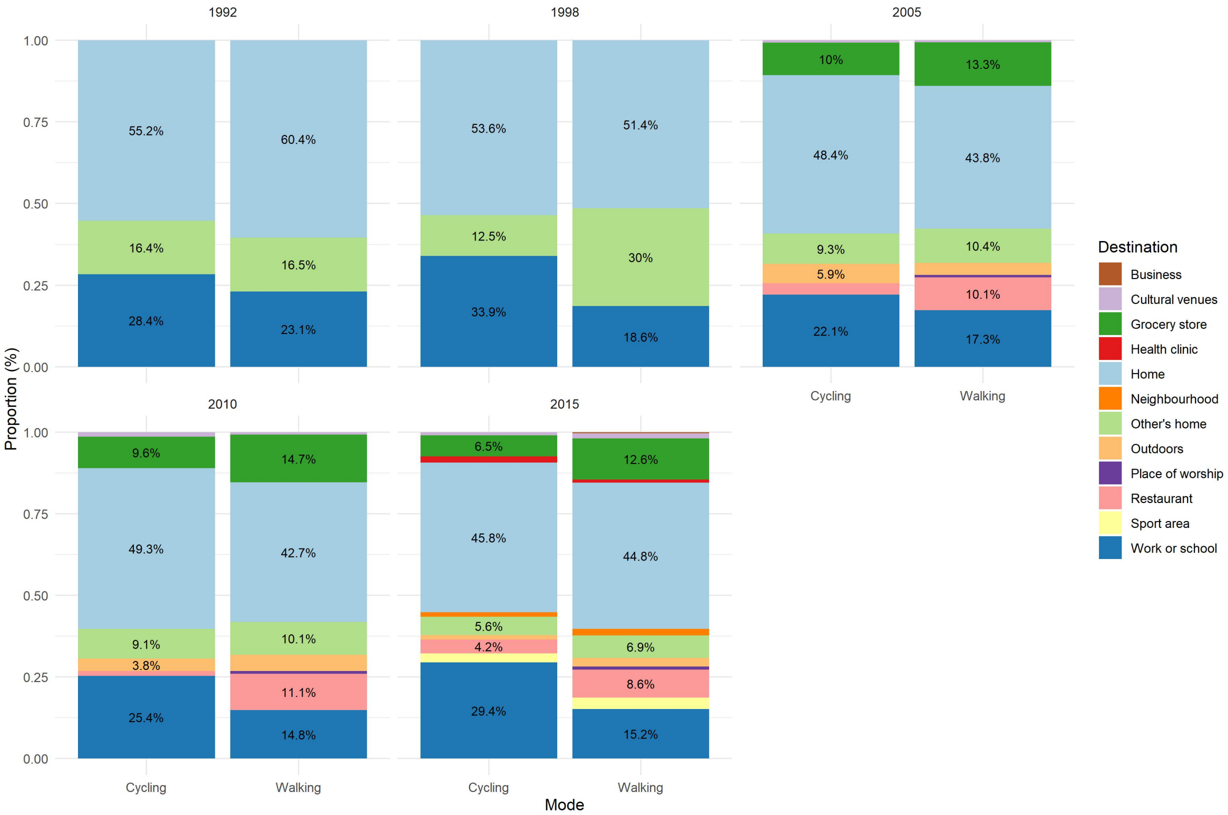

Figure 1: Percentage of walking and cycling trips categorized by destination and year

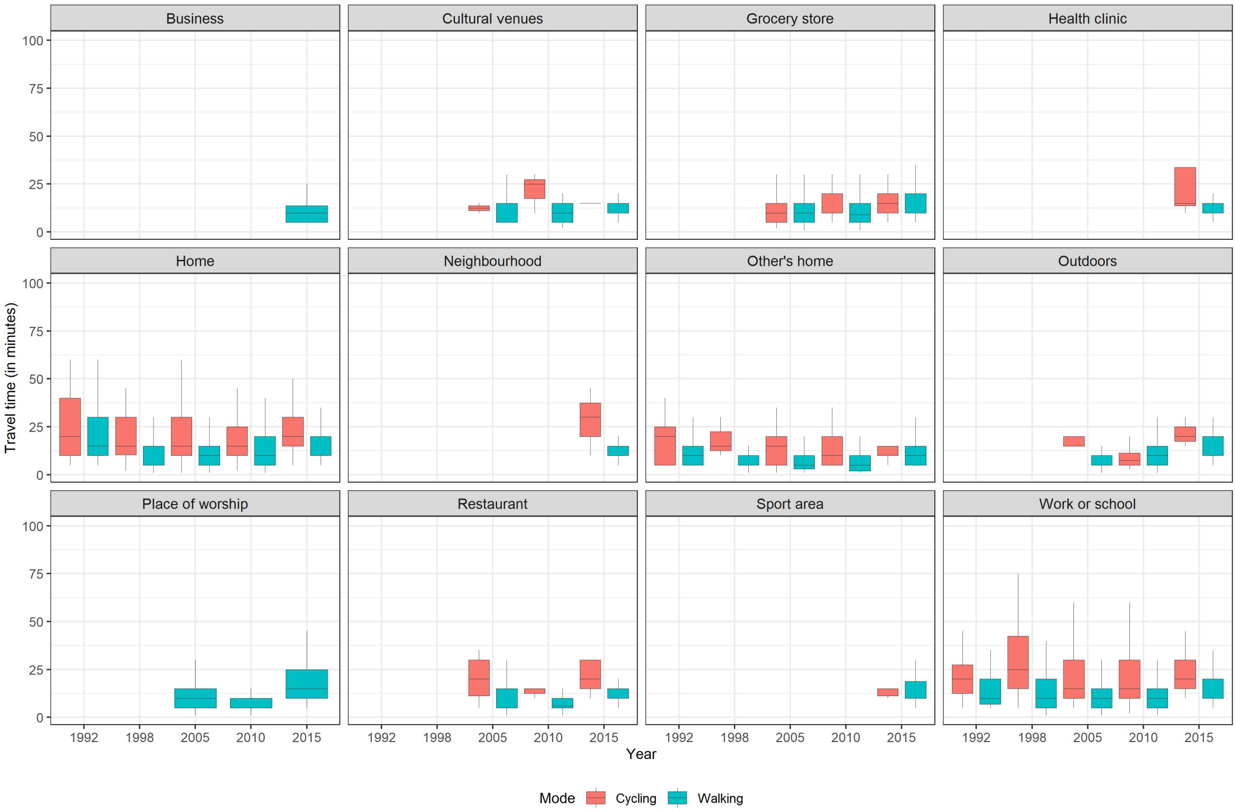

Figure 2: Percentage of walking trips categorized by origin and destination

surveys to 15 minutes by 2015. Other destinations remained with a constant travel time.

Figures 3 and 4 show walking and cycling trips from 1992 to 2015 through heat maps. These maps use color gradients to represent the percentage of trips between origins and destinations, with darker colors indicating higher percentages and lighter colors representing less frequent routes. In 1992, walking trips with 'Home' as both the origin and destination made up the majority, accounting for almost 31% of all walking trips. These trips often involved leisure activities, like short walks or dog walking. Following this, trips from 'Home' to 'Work or school' comprised 18% of walking trips. Overall, 'Home' is the principal hub, either as an origin or destination, with only 5% of trips not involving 'Home.' By 1998, more than half of walking trips were between 'Home' and 'Other's home,' with 'Home' to 'Other's home' and 'Other's home' to 'Home' each representing 26% of trips. During this year, 'Home' to 'Home' accounted for only 10% of trips. In 2005, trips with origins or destinations involving 'Home' and 'Work or school' remained as the most common, but the introduction of new destinations led to a more dispersed trip distribution. Together, these two combinations accounted for 25% of all trips. In 2010, trips between 'Home' and 'Work or school' continued as the most common type, representing 18% of trips, tied with trips from 'Grocery store' to 'Home' (9%). Finishing the walking trip descriptive analysis, in 2015, the highest proportion of trips were from 'Home' to 'Work or school' (12%) and vice versa (11%). Trips from 'Home' to 'Home' accounted for 8% of trips, and 'Grocery store' became a notable destination for trips originating from 'Home' (8%).

For cycling trips (Figure 4), in 1992, the most common trip was from 'Home' to 'Work or school' (26%), followed by trips from 'Other's home' to 'Home' (22%). In all following years, the most frequent trip were between 'Home' and 'Work or school' in both direction. This combination accounted for 65% of the trips in 1998, 40% in 2005, 52% in 2010, and 58% in 2015. Additionally and unlike walking trips, 'Home' to

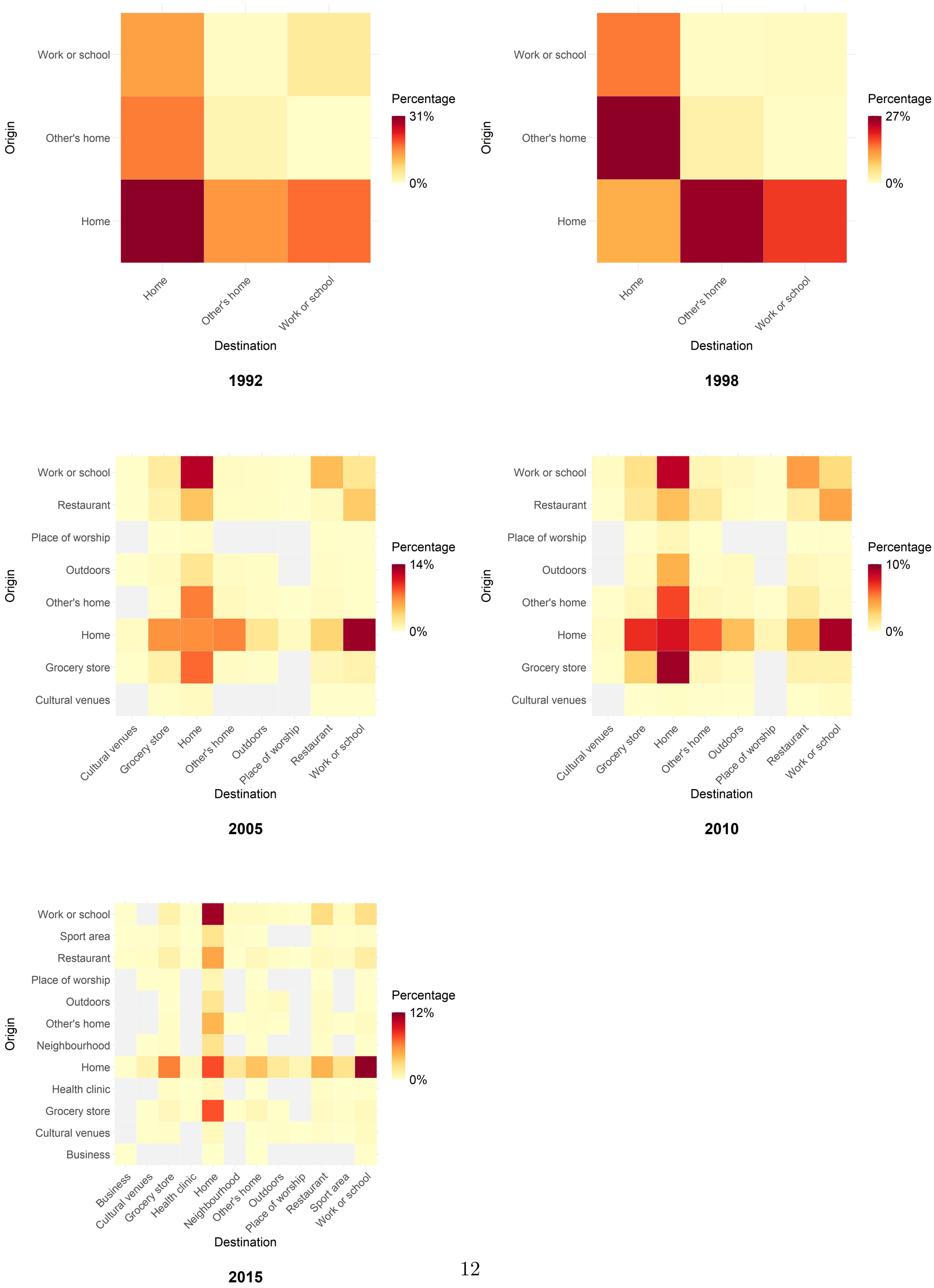

Figure 3: Percentage of walking trips categorized by origin and destination

‘Home’ trips were not a common cycling trip in any of the surveys. This suggests that leisure trips, such as activities around the home, are predominantly done by foot rather than by bicycle.

3.4. Calibrated impedance function

This section presents the identified impedance functions for walking and cycling trips to various destinations across Canadian Metropolitan and Census Agglomeration Areas from 1992 to 2015. In general, the impedance functions aim to capture transportation behavior, illustrating that the likelihood of traveling between two points decreases as travel duration increases. Each impedance function follows one of the mathematical equations previously mentioned, enabling the plotting of PDF curves. These curves also highlight critical points at which a person’s tendency to walk or cycle significantly decreases.

As explained in the methodology section, we used the {fitdistrplus} package to calibrate the functions. We selected the best impedance function for each transportation mode, destination, and year based on the lowest AIC value. The AIC metric not only assesses the goodness of fit but also penalizes model complexity to prevent overfitting. AIC provides a balance between a model’s accuracy and simplicity, with lower values indicating a more economical model. The distribution with the lowest AIC was considered the most suitable for representing the distance decay curve for each specific destination in each year. We chose AIC as the selection criterion because, while the {fitdistrplus} package accommodates weighted episodes during estimation, it does not extend this functionality to diagnostic plots, which are typically unweighted and traditionally used to select the best-fitting function.

In total, we fitted 64 impedance functions. Among the candidate distributions, only the lognormal, gamma, and uniform distributions were selected using our methodology, with the uniform distribution being chosen exclusively for certain cycling destinations. The absence of exponential functions, given the variety of destinations, year and mode of transport, indicates that the impendance functions applied in active accessibility studies may not be adequately measuring travel behavior. Table **??** displays the selected functions for walking trips, while Table **??** presents the functions for cycling trips. Appendix A includes the AIC, BIC, and log-likelihood values for all candidate distributions.

Figure X presents the calibrated functions for the destination “Outdoors,” along with a histogram of the empirical distribution of trips, split by year and transportation mode. Comparing functions from different categories can be tricky when analyzed for the first time, but by starting with the functions from the walking transportation mode, the calibrated functions from this example show a similar pattern. At a duration of around zero minutes, the probability of making the trip is low (with a density of zero for the years 2010 and 2015). After a few minutes, there is a peak in the maximum probability of traveling to reach “Outdoors,” followed by a drop in willingness to zero for very high values of time, indicating a low probability of making the trip.

For the years 2005 and 2010, the selected impedance functions are of the gamma type, with shapes of $\alpha = 1.24$ and $\alpha = 1.27$, respectively, and the same rate of $\sigma = 0.13$. The rate parameter (σ) mainly controls the speed of the curved drop, which is the same for both years. The shape parameter (μ) controls how the density peak shifts in relation to the x-axis (the travel time). A larger shape value means that the probability peak occurs at larger values of time. Since the shape values for 2005 and 2010 are very close, the peak of the PDF curve in both cases occurs at 2 minutes. Although the difference in shape (μ) between the two years is small and does not change the time at which the peak occurs, it is enough to cause a difference in the peak values themselves. In 2005, the walking trips had a higher density around 2 minutes (0.079) compared to 2010 (0.077).

For 2015, the PDF that best represents the population’s transport behavior is a lognormal distribution, with a mean of $\mu = 3.08$ and a standard deviation of $\sigma = 0.80$. In this year, the density peak (0.05) occurs when the journey has the duration of 7 minutes. Here, we can see that a lower density peak also corresponds to a more dispersed curve, with higher densities at larger values of time. In fact, while in 2005 and 2010 walking trips had densities close to zero for values over 50 minutes, in 2015 there is still a small density (0.002) at the 50-minute mark.

For trips made by bicycle, in 2015 and 2010 the impedance functions are of the gamma type, with a shape of $\alpha = 2.99$ and $\alpha = 2.05$, respectively, and rates $\sigma = 0.17$ and $\sigma = 0.59$. Such configurations in

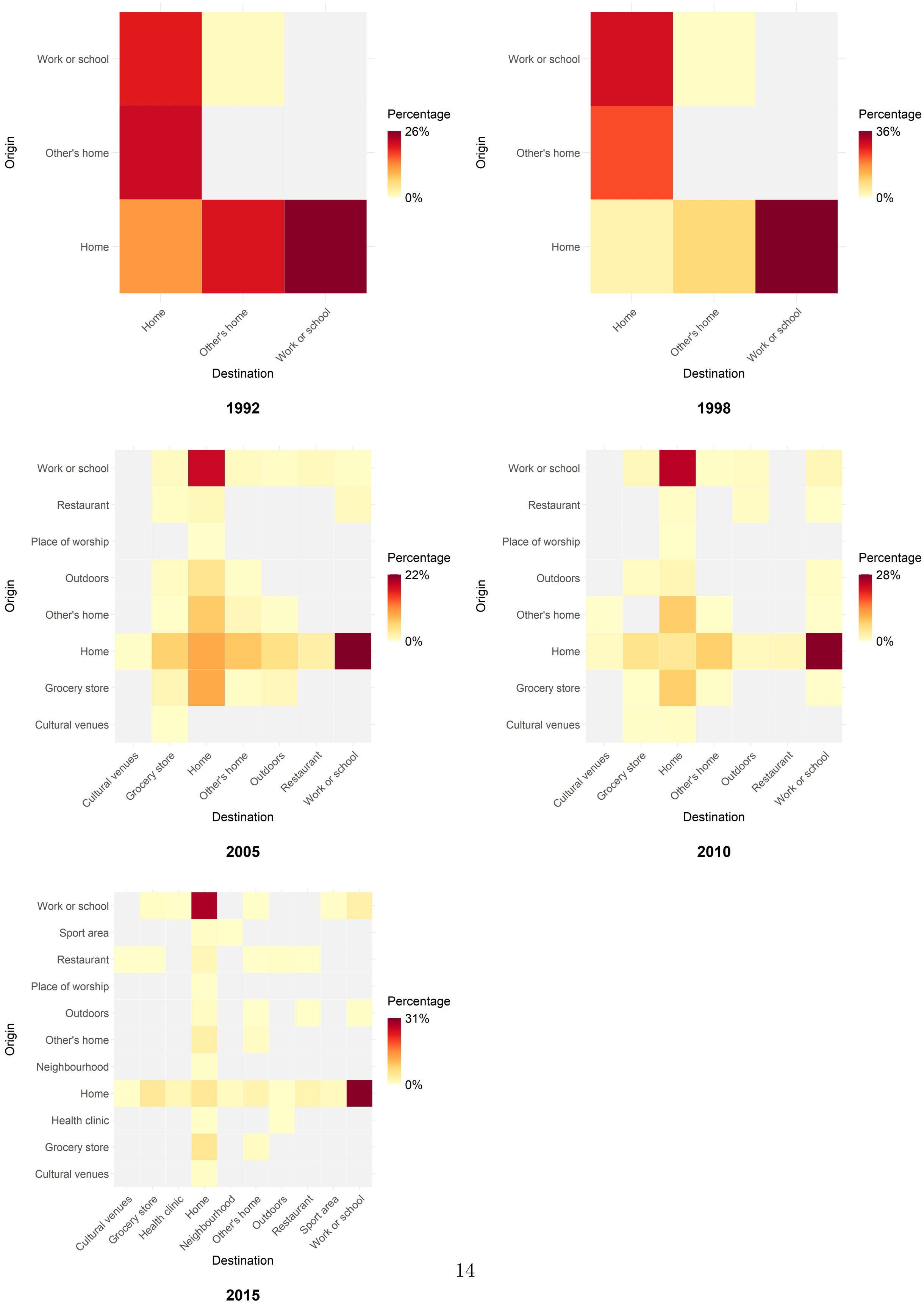

Figure 4: Percentage of walking trips categorized by origin and destination

Table 3: Impedance functions and AIC for walking trips.

Year	Destination	Impedance function	Parameter 1*	Parameter 2*	AIC	Count
1992	Home	Lognormal	2.92	0.77	7761103	296
1992	Other's home	Lognormal	2.15	0.84	1778150	81
1992	Work or school	Lognormal	2.38	0.70	2319400	113
1998	Home	Lognormal	2.07	0.92	5656275	302
1998	Other's home	Lognormal	1.75	0.97	2892771	176
1998	Work or school	Gamma	1.23	0.09	2318752	109
2005	Cultural venues	Gamma	4.10	0.34	238506	25
2005	Grocery store	Gamma	1.22	0.10	4776215	558
2005	Home	Gamma	1.16	0.08	17291041	1831
2005	Other's home	Gamma	1.03	0.11	3420742	436
2005	Outdoors	Gamma	1.24	0.13	1272012	155
2005	Place of worship	Gamma	2.07	0.19	228307	32
2005	Restaurant	Lognormal	1.95	0.79	3727576	421
2005	Work or school	Lognormal	2.13	0.79	8182691	724
2010	Cultural venues	Gamma	3.60	0.34	304141	25
2010	Grocery store	Lognormal	2.08	0.85	6369652	489
2010	Home	Gamma	1.10	0.07	19584386	1424
2010	Other's home	Lognormal	1.81	0.92	4035574	336
2010	Outdoors	Gamma	1.27	0.13	2114346	167
2010	Place of worship	Lognormal	1.95	0.70	285177	28
2010	Restaurant	Lognormal	2.01	0.90	5187191	371
2010	Work or school	Lognormal	2.21	0.78	7917431	494
2015	Business	Lognormal	2.41	0.67	102286	8
2015	Cultural venues	Gamma	4.57	0.34	543242	43
2015	Grocery store	Lognormal	2.48	0.68	4001111	338
2015	Health clinic	Lognormal	2.44	0.70	324578	27
2015	Home	Lognormal	2.57	0.74	17235960	1202
2015	Neighbourhood	Lognormal	2.41	0.77	981626	53
2015	Other's home	Lognormal	2.43	0.80	2388598	186
2015	Outdoors	Lognormal	2.54	0.79	1247963	72
2015	Place of worship	Gamma	5.64	0.28	343187	24
2015	Restaurant	Lognormal	2.38	0.74	3490082	231
2015	Sport area	Lognormal	2.48	0.59	1199687	94
2015	Work or school	Lognormal	2.55	0.64	6612061	407

Note:
For 'lnorm' distributions, 'Parameter 1' and 'Parameter 2' refer to the mean and standard deviation of the distribution on the logarithmic scaler, respectively. For the 'Gamma' distribution, 'Parameter 1' and 'Parameter 2' refer to the rate and shape of the distribution, respectively. For the 'Uniform' distribution, 'Parameter 1' refers to the minimum lower bound and 'Parameter 2' refers to the upper bound (maximum) of the distribution. 'AIC' means Akaike information criterion.

Table 4: Impedance functions and AIC for cycling trips.

Year	Destination	Impedance function	Parameter 1*	Parameter 2*	AIC	Count
1992	Home	Gamma	1.18	0.05	1018747	37
1992	Other's home	Lognormal	2.57	0.82	373451	11
1992	Work or school	Gamma	3.00	0.17	433582	19
1998	Home	Gamma	1.70	0.07	715802	30
1998	Other's home	Lognormal	2.79	0.80	113905	7
1998	Work or school	Gamma	3.37	0.10	481536	19
2005	Cultural venues	Uniform	0.00	15.13	6355	2
2005	Grocery store	Gamma	1.93	0.14	320218	29
2005	Home	Gamma	1.49	0.07	1794317	140
2005	Other's home	Gamma	1.84	0.15	310058	27
2005	Outdoors	Gamma	2.99	0.17	215894	17
2005	Restaurant	Gamma	3.37	0.21	109072	10
2005	Work or school	Lognormal	2.93	0.70	888655	64
2010	Cultural venues	Uniform	0.00	32.58	38938	3
2010	Grocery store	Lognormal	2.68	0.61	315037	20
2010	Home	Lognormal	2.60	0.77	2006242	103
2010	Other's home	Lognormal	2.40	0.63	338777	19
2010	Outdoors	Lognormal	2.05	0.59	92699	8
2010	Restaurant	Uniform	0.00	17.49	35370	3
2010	Work or school	Lognormal	2.65	0.77	1292760	53
2015	Cultural venues	Lognormal	2.71	0.00	-Inf	2
2015	Grocery store	Lognormal	3.08	0.80	229413	14
2015	Health clinic	Lognormal	2.93	0.86	80810	4
2015	Home	Lognormal	3.08	0.61	1745846	98
2015	Neighbourhood	Uniform	0.00	48.55	49924	3
2015	Other's home	Lognormal	2.52	0.44	140210	12
2015	Outdoors	Uniform	0.00	35.03	31463	3
2015	Restaurant	Lognormal	3.11	0.60	115406	9
2015	Sport area	Uniform	0.00	17.47	32969	6
2015	Work or school	Lognormal	3.03	0.41	1162876	63

Note:
For 'lnorm' distributions, 'Parameter 1' and 'Parameter 2' refer to the mean and standard deviation of the distribution on the logarithmic scaler, respectively. For the 'Gamma' distribution, 'Parameter 1' and 'Parameter 2' refer to the rate and shape of the distribution, respectively. For the 'Uniform' distribution, 'Parameter 1' refers to the minimum lower bound and 'Parameter 2' refers to the upper bound (maximum) of the distribution. 'AIC' means Akaike information criterion.

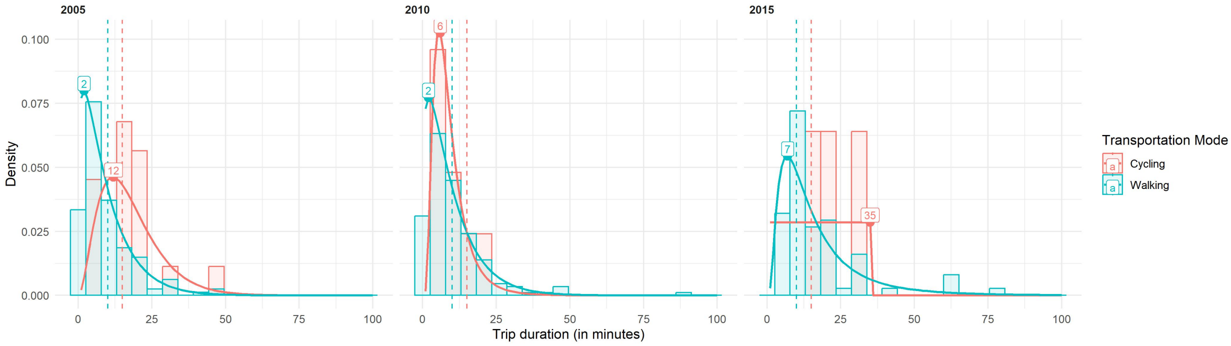

Figure 5: Empirical data and impedance functions fitted for walking trips with ‘work or school‘ as destination.

the gamma function result in different peak values, where in 2005 the peak (0.046) of density occurred in 12 minutes, in 2010 the peak (0.102) occurs in 6 minutes, half the previous time. In 2005, the curve has a smaller peak and is more dispersed, while in 2010 the curve has a larger peak and is less dispersed, reinforced by its higher σ rate.

In 2005, the PDF that best represented the curve was a uniform function with upper bound equals to 35 minutes and peak of (0.028). The presence of uniform functions means that it wasn't possible to parameterize more complex functions (like the other functions) and is explained by the low number of episodes in this category of destination, mode of transport and year (in this case, there were only 3 episodes identified). Overall, all the uniform functions have a maximum of 6 episodes and all of them are for the transportation mode cycling - which can be explained since this mode of transport doesn't have many episodes compared to the walking episodes. The figure also shows how cycling trips tend to have greater dispersion and higher typical values (dashed vertical lines) when compared to walking trips.

This temporal difference between the decay functions is also evident in Figure (temp-evolution-by-destination), which shows the calibrated functions for each year of analysis across all destination and transport mode categories for walking trips. For some locations, the impedance functions are of the same type and have similar parameters across all the years analyzed. For example, the “Cultural venues” destination consistently uses a gamma function to represent the population's transport behavior for all the years analyzed. On the other hand, the “Place of worship” destination exhibits temporal differences, with distinctly different peaks and density dispersions, reflecting the variations in the empirical data shown in Figure 2 and discussed above.

Only destinations that appear in more than one year can have their temporal evolution analyzed. Because of this, for the twelve possible destinations in the cycling mode, only seven locations can be temporally analyzed: “Cultural venues,” “Grocery store,” “Home,” “Other's home,” “Outdoors,” “Restaurant,” and “Work or school.” In the case of the walking trips, this transporation mode is present in more than one survey for the same locations as cycling mode, as well as for “Place of worship.”

After performing the Kruskal-Wallis test (to assess whether there was a statistically significant difference between the distributions of empirical travel time values, considering the time differences for each destination) and the pairwise Wilcoxon test, we were able to identify the destinations where a statistically significant difference was detected. Table **??** shows only the destinations where a statistically significant difference was found, considering the two modes of active transport analyzed.

For cycling trips, the destinations “Home,” “Grocery store,” “Restaurant,” and “Work or school” had at least one year with a statistically significant difference. For example, for the “Home” destination, there was a statistically significant difference between 1992 and 2005 (p-value = 0.0046), 1992 and 2010 (p-value = 0.0003), 1998 and 2005 (p-value = 0.0390), 1998 and 2010 (p-value = 0.0412), 1998 and 2015 (p-value = 0.0196), 2005 and 2010 (p-value = 0.00017), and 2010 and 2015 (p-value = 0.01008).

For walking trips, among the destinations with a potential time difference, only “Cultural venues” did not show a statistically significant difference during the period analyzed. As a result, among the destinations

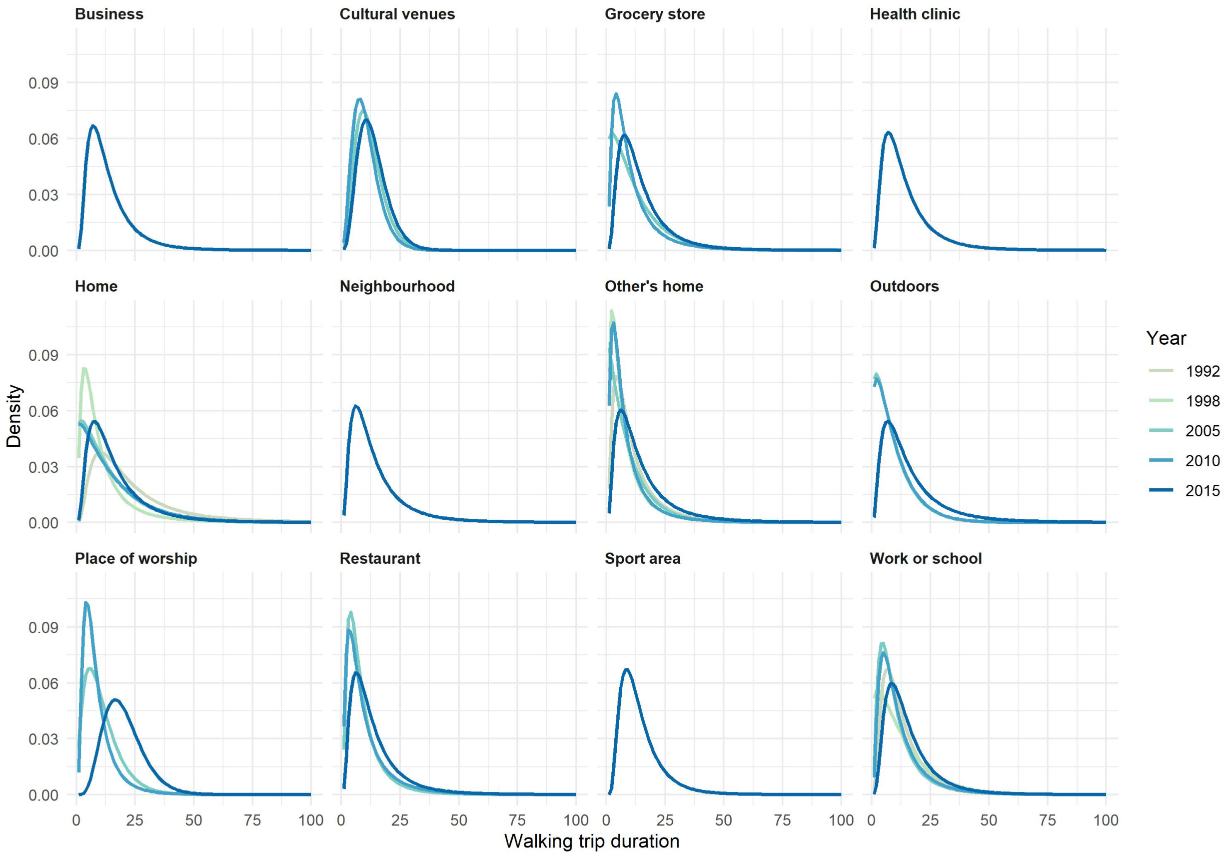

Figure 6: Temporal evolution of walking impedance functions.

Table 5: P-values of the pairwise Wilcoxon test .

Mode	Destination	Year	1992	1998	2005	2010
Walking	Restaurant	2010	NA	NA	0.00003	NA
Walking	Restaurant	2015	NA	NA	0.00003	0.00001
Walking	Grocery store	2010	NA	NA	0.00000	NA
Walking	Grocery store	2015	NA	NA	NA	0.00159
Walking	Home	1998	0.00000	NA	NA	NA
Walking	Home	2005	0.00000	0.00000	NA	NA
Walking	Home	2010	0.00000	0.00000	0.00000	NA
Walking	Home	2015	0.00000	0.00000	0.00000	NA
Walking	Work or school	1998	0.00871	NA	NA	NA
Walking	Work or school	2015	NA	0.00004	0.00483	NA
Walking	Other's home	1998	0.00000	NA	NA	NA
Walking	Other's home	2010	0.00003	0.01048	0.04166	NA
Walking	Other's home	2015	NA	0.00000	0.00000	0.00000
Walking	Place of worship	2015	NA	NA	0.01946	NA
Walking	Outdoors	2015	NA	NA	0.00000	0.00044
Cycling	Restaurant	2010	NA	NA	0.03883	NA
Cycling	Restaurant	2015	NA	NA	NA	0.04323
Cycling	Home	2005	0.00460	0.03902	NA	NA
Cycling	Home	2010	0.00030	0.04117	0.00017	NA
Cycling	Home	2015	NA	0.01960	NA	0.01008
Cycling	Work or school	1998	0.02112	NA	NA	NA
Cycling	Work or school	2005	NA	0.03558	NA	NA
Cycling	Work or school	2015	NA	0.00190	0.00242	0.00290
Cycling	Grocery store	2015	NA	NA	0.00278	NA

appearing in more than one GSS survey, only "Cultural venues" showed no statistical evidence of temporal evolution for any of the modes of transport. Four destinations ("Home," "Grocery store," "Restaurant," and "Work or school") exhibited statistical differences for both modes of transport.

Finally, Figures 7 and 8 present the impedance functions for different destination categories, grouped by year, for the walking and cycling modes of transport, respectively.

3.5. Conclusion

References

Apparicio, Philippe, Mohamed Abdelmajid, Mylene Riva, and Richard Shearmur. 2008. "Comparing Alternative Approaches to Measuring the Geographical Accessibility of Urban Health Services: Distance Types and Aggregation-Error Issues." *International Journal of Health Geographics* 7 (1): 1–14.

Arranz-Lopez, Aldo, Julio A Soria-Lara, Frank Witlox, and Antonio Paez. 2019. "Measuring Relative Non-Motorized Accessibility to Retail Activities." *International Journal of Sustainable Transportation* 13 (9): 639–51.

Bhat, Chandra, Susan Handy, Kara Kockelman, Hani Mahmassani, Anand Gopal, Issam Srour, and Lisa Weston. 2002. "Development of an Urban Accessibility Index: Formulations, Aggregation, and Application." *Work* 4938 (4).

Carrothers, Gerald AP. 1956. "An Historical Review of the Gravity and Potential Concepts of Human Interaction." *Journal of the American Institute of Planners* 22 (2): 94–102.

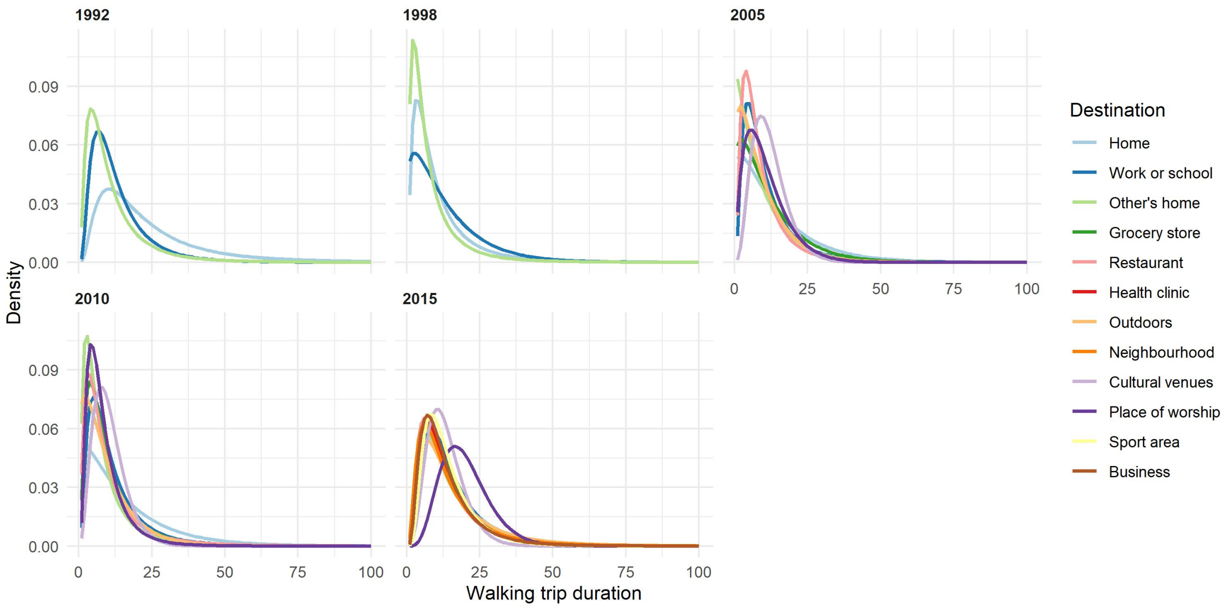

Figure 7: Walking functions grouped by year.

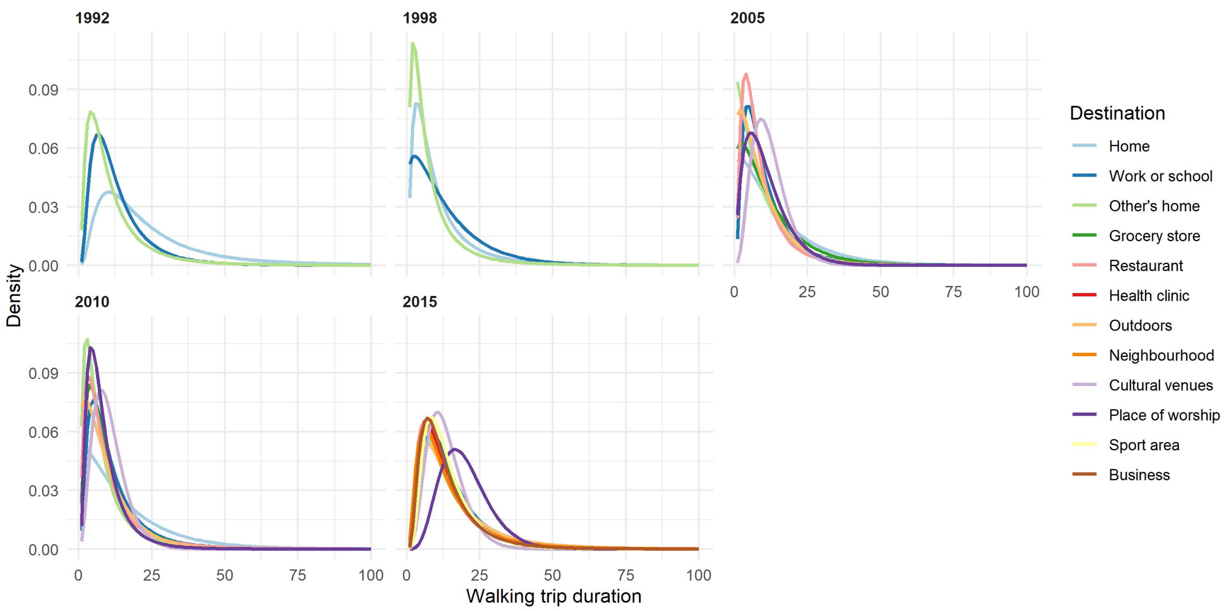

Figure 8: Cycling functions grouped by year.

Cascetta, Ennio, Armando Carteni, and Marcello Montanino. 2013. "A New Measure of Accessibility Based on Perceived Opportunities." *Procedia-Social and Behavioral Sciences* 87: 117–32.

Church, Richard L, and James R Marston. 2003. "Measuring Accessibility for People with a Disability." *Geographical Analysis* 35 (1): 83–96.

Clifton, KELLY J, and SL Handy. 2001. "Evaluating Neighborhood Accessibility: Possibilities and Practicalities." *Journal of Transportation and Statistics* 4 (2-3): 67.

Currie, Graham. 2010. "Quantifying Spatial Gaps in Public Transport Supply Based on Social Needs." *Journal of Transport Geography* 18 (1): 31–41.

De Vries, Jacob J, Peter Nijkamp, and Piet Rietveld. 2009. "Exponential or Power Distance-Decay for Commuting? An Alternative Specification." *Environment and Planning A* 41 (2): 461–80.

Dunn, William L., and J. Kenneth Shultis. 2023. "Appendix a - Some Common Probability Distributions." In, edited by William L. Dunn and J. Kenneth Shultis, 447–95. Elsevier. `https://doi.org/10.1016/B978-0-12-819739-4.00019-6`.

Eldridge, J Douglas, and John Paul Jones III. 1991. "Warped Space: A Geography of Distance Decay." *The Professional Geographer* 43 (4): 500–511.

Fotheringham, A Stewart. 1981. "Spatial Structure and Distance-Decay Parameters." *Annals of the Association of American Geographers* 71 (3): 425–36.

Fotheringham, A Stewart, and Morton E O'Kelly. 1989. *Spatial Interaction Models: Formulations and Applications*. Vol. 1. Kluwer Academic Publishers Dordrecht.

Frank, Lawrence D, and Peter O Engelke. 2001. "The Built Environment and Human Activity Patterns: Exploring the Impacts of Urban Form on Public Health." *Journal of Planning Literature* 16 (2): 202–18.

Frank, Lawrence D, Thomas L Schmid, James F Sallis, James Chapman, and Brian E Saelens. 2005. "Linking Objectively Measured Physical Activity with Objectively Measured Urban Form: Findings from SMARTRAQ." *American Journal of Preventive Medicine* 28 (2): 117–25.

Geurs, Karst. 2006. *Accessibility, Land Use and Transport: Accessibility Evaluation of Land-Use and Transport Developments and Policy Strategy*. Eburon Uitgeverij BV.

Geurs, Karst T, and Jan R Ritsema van Eck. 2001. "Accessibility Measures: Review and Applications. Evaluation of Accessibility Impacts of Land-Use Transportation Scenarios, and Related Social and Economic Impact." *RIVM Rapport 408505006*.

Geurs, Karst T, and Bert Van Wee. 2004. "Accessibility Evaluation of Land-Use and Transport Strategies: Review and Research Directions." *Journal of Transport Geography* 12 (2): 127–40.

Grengs, Joe. 2015. "Nonwork Accessibility as a Social Equity Indicator." *International Journal of Sustainable Transportation* 9 (1): 1–14.

Gutierrez, Javier, Rafael Gonzalez, and Gabriel Gomez. 1996. "The European High-Speed Train Network: Predicted Effects on Accessibility Patterns." *Journal of Transport Geography* 4 (4): 227–38.

Handy, Susan. 1993. "Regional Versus Local Accessibility: Implications for Nonwork Travel."

Handy, Susan L, and Debbie A Niemeier. 1997. "Measuring Accessibility: An Exploration of Issues and Alternatives." *Environment and Planning A* 29 (7): 1175–94.

Hansen, Walter G. 1959. "How Accessibility Shapes Land Use." *Journal of the American Institute of Planners* 25 (2): 73–76.

Hino, Adriano AF, Rodrigo S Reis, Olga L Sarmiento, Diana C Parra, and Ross C Brownson. 2014. "Built Environment and Physical Activity for Transportation in Adults from Curitiba, Brazil." *Journal of Urban Health* 91: 446–62.

Hsiao, Shirley, Jian Lu, James Sterling, and Matthew Weatherford. 1997. "Use of Geographic Information System for Analysis of Transit Pedestrian Access." *Transportation Research Record* 1604 (1): 50–59.

Hull, Angela, Cecilia Silva, and Luca Bertolini. 2012. *Accessibility Instruments for Planning Practice*. Cost Office Brussels.

Iacono, Michael, Kevin J Krizek, and Ahmed El-Geneidy. 2010. "Measuring Non-Motorized Accessibility: Issues, Alternatives, and Execution." *Journal of Transport Geography* 18 (1): 133–40.

Iacono, Michael, Kevin Krizek, and Ahmed M El-Geneidy. 2008. "Access to Destinations: How Close Is Close Enough? Estimating Accurate Distance Decay Functions for Multiple Modes and Different Purposes."

ITF. 2017. *Linking People and Places: New Ways of Understanding Spatial Access in Cities.* OECD Publishing.

Kanafani, Adib. 1983. "Transportation Demand Analysis."

Koenig, Jean-Gerard. 1980. "Indicators of Urban Accessibility: Theory and Application." *Transportation* 9 (2): 145–72.

Krizek, Kevin J. 2005. "Perspectives on Accessibility and Travel." In *Access to Destinations*, 109–30. Emerald Group Publishing Limited.

Kwan, Mei-Po. 1998. "Space-Time and Integral Measures of Individual Accessibility: A Comparative Analysis Using a Point-Based Framework." *Geographical Analysis* 30 (3): 191–216.

Kwan, Mei-Po, Alan T Murray, Morton E OKelly, and Michael Tiefelsdorf. 2003. "Recent Advances in Accessibility Research: Representation, Methodology and Applications." *Journal of Geographical Systems* 5: 129–38.

Lamiquiz, Patxi J, and Jorge Lopez-Dominguez. 2015. "Effects of Built Environment on Walking at the Neighbourhood Scale. A New Role for Street Networks by Modelling Their Configurational Accessibility?" *Transportation Research Part A: Policy and Practice* 74: 148–63.

Larsen, Jacob, Ahmed El-Geneidy, and Farhana Yasmin. 2010. "Beyond the Quarter Mile: Re-Examining Travel Distances by Active Transportation." *Canadian Journal of Urban Research* 19 (1): 70–88.

Levinson, David M, and Kevin J Krizek. 2005. *Access to Destinations.* Elsevier Publishers.

Li, Aoyong, Yizhe Huang, and Kay W Axhausen. 2020. "An Approach to Imputing Destination Activities for Inclusion in Measures of Bicycle Accessibility." *Journal of Transport Geography* 82: 102566.

Lowry, M, Daniel Callister, M Gresham, and B Moore. 2012. "Using Bicycle Level of Service to Assess Community-Wide Bikeability." In *91st Annual Meeting of the Transportation Research Board, Washington, DC: Transportation Research Board.*

Luoma, Martti, Kauko Mikkonen, and Mauri Palomaki. 1993. "The Threshold Gravity Model and Transport Geography: How Transport Development Influences the Distance-Decay Parameter of the Gravity Model." *Journal of Transport Geography* 1 (4): 240–47.

Meyer, Michael D, and Eric J Miller. 1984. "Urban Transportation Planning: A Decision-Oriented Approach."

Mikkonen, Kauko, and Martti Luoma. 1999. "The Parameters of the Gravity Model Are Changing–How and Why?" *Journal of Transport Geography* 7 (4): 277–83.

Miller, Harvey J. 2005. "Place-Based Versus People-Based Accessibility." In *Access to Destinations*, 63–89. Emerald Group Publishing Limited.

Millward, Hugh, Jamie Spinney, and Darren Scott. 2013. "Active-Transport Walking Behavior: Destinations, Durations, Distances." *Journal of Transport Geography* 28: 101–10.

Nassir, Neema, Mark Hickman, Ali Malekzadeh, and Elnaz Irannezhad. 2016. "A Utility-Based Travel Impedance Measure for Public Transit Network Accessibility." *Transportation Research Part A: Policy and Practice* 88: 26–39.

Osth, John, Johan Lyhagen, and Aura Reggiani. 2016. "A New Way of Determining Distance Decay Parameters in Spatial Interaction Models with Application to Job Accessibility Analysis in Sweden." *European Journal of Transport and Infrastructure Research* 16 (2).

Paez, Antonio, Darren M Scott, and Catherine Morency. 2012. "Measuring Accessibility: Positive and Normative Implementations of Various Accessibility Indicators." *Journal of Transport Geography* 25: 141–53.

Papa, Enrica, and Pierluigi Coppola. 2012. "Gravity-Based Accessibility Measures for Integrated Transport-Land Use Planning (GraBAM)." *Accessibility Instruments for Planning Practice* 117: 124.

Pirie, Gordon H. 1979. "Measuring Accessibility: A Review and Proposal." *Environment and Planning A* 11 (3): 299–312.

Prins, Richard G, Frank Pierik, Astrid Etman, Reinier P Sterkenburg, Carlijn BM Kamphuis, and FJ Van Lenthe. 2014. "How Many Walking and Cycling Trips Made by Elderly Are Beyond Commonly Used Buffer Sizes: Results from a GPS Study." *Health & Place* 27: 127–33.

Reggiani, Aura, Pietro Bucci, and Giovanni Russo. 2011. "Accessibility and Impedance Forms: Empirical Applications to the German Commuting Network." *International Regional Science Review* 34 (2): 230–

52.
Saghapour, Tayebeh, Sara Moridpour, and Russell G Thompson. 2017. "Measuring Cycling Accessibility in Metropolitan Areas." *International Journal of Sustainable Transportation* 11 (5): 381–94.
Sallis, James F, Lawrence D Frank, Brian E Saelens, and M Katherine Kraft. 2004. "Active Transportation and Physical Activity: Opportunities for Collaboration on Transportation and Public Health Research." *Transportation Research Part A: Policy and Practice* 38 (4): 249–68.
Signorino, Guido, Roberto Pasetto, Elisa Gatto, Massimo Mucciardi, Marina La Rocca, and Pierpaolo Mudu. 2011. "Gravity Models to Classify Commuting Vs. Resident Workers. An Application to the Analysis of Residential Risk in a Contaminated Area." *International Journal of Health Geographics* 10 (1): 1–10.
Skov-Petersen, Hans. 2001. "Estimation of Distance-Decay Parameters: GIS-Based Indicators of Recreational Accessibility." In *ScanGIS*, 237–58.
Song, Shunfeng. 1996. "Some Tests of Alternative Accessibility Measures: A Population Density Approach." *Land Economics*, 474–82.
Sun, Guibo, Hui Lin, and Rongrong Li. 2012. "Measuring the Influence of Built Environment on Walking Behavior: An Accessibility Approach." In *Geographic Information Science: 7th International Conference, GIScience 2012, Columbus, OH, USA, September 18-21, 2012. Proceedings 7*, 187–97. Springer.
Taylor, Peter. 1975. "Distance Decay Models in Spatial Interactions." *(No Title)*.
Untermann, Richard K. 1984. "Accommodating the Pedestrian: Adapting Towns and Neighbourhoods for Walking and Bicycling."
Vale, David S, and Mauro Pereira. 2017. "The Influence of the Impedance Function on Gravity-Based Pedestrian Accessibility Measures: A Comparative Analysis." *Environment and Planning B: Urban Analytics and City Science* 44 (4): 740–63.
Vandenbulcke, Gregory, Therese Steenberghen, and Isabelle Thomas. 2009. "Mapping Accessibility in Belgium: A Tool for Land-Use and Transport Planning?" *Journal of Transport Geography* 17 (1): 39–53.
Vasconcelos, Ana S, and Tiago L Farias. 2012. "Evaluation of Urban Accessibility Indicators Based on Internal and External Environmental Costs." *Transportation Research Part D: Transport and Environment* 17 (6): 433–41.
Vega, Amaya. 2012. "Using Place Rank to Measure Sustainable Accessibility." *Journal of Transport Geography* 24: 411–18.
Vickerman, Roger W. 1974. "Accessibility, Attraction, and Potential: A Review of Some Concepts and Their Use in Determining Mobility." *Environment and Planning A* 6 (6): 675–91.
Wu, Xueying, Yi Lu, Yaoyu Lin, and Yiyang Yang. 2019. "Measuring the Destination Accessibility of Cycling Transfer Trips in Metro Station Areas: A Big Data Approach." *International Journal of Environmental Research and Public Health* 16 (15): 2641.
Yang, Yong, and Ana V Diez-Roux. 2012. "Walking Distance by Trip Purpose and Population Subgroups." *American Journal of Preventive Medicine* 43 (1): 11–19.
Zhao, Fang, Lee-Fang Chow, Min-Tang Li, Ike Ubaka, and Albert Gan. 2003. "Forecasting Transit Walk Accessibility: Regression Model Alternative to Buffer Method." *Transportation Research Record* 1835 (1): 34–41.