A historical analysis of the evolution of active travel behaviour in Canada

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Abstract

Impedance functions are used to represent travel behaviour due to their potential to capture traveler responses to geographic distance between origins and destinations. Focusing our analysis on active transportation modes in Canadian metropolitan regions, this study has as objectives to provide an historical overview of active mobility in terms of main origins, destinations and travel time of walking and cycling trips, and to identify appropriate impedance functions for active transportation modes considering a wide range of destinations and time periods. To achieve these objectives, this paper analyzed more than cases of 12,000 active transportation episodes, that represented more than 12 million episodes, from the Canadian General Social Survey (GSS) from 1992 to 2015. This study confirmed that for walking trips, typical travel times remained constant at 10 minutes since 2005, while for cycling trips, typical travel times fluctuated, declining from 20 minutes in 1992 to 10 minutes in 2010 before increasing to 20 minutes in 2015. For walking trips, findings indicate that 'Home' continues to be the main hub, either as an origin or destination. For cycling trips, the combination of 'Home' and 'Work or school' accounted for most of the trips. Additionally, we fitted 64 impedance functions for twelve destinations and over 20 years. The results indicate that none of the parameterized functions were exponential, suggesting that the impedance functions commonly used in active accessibility studies may not accurately capture travel behavior, especially for very short trips, giving shorter trips a higher probability of being made. The estimated impedance functions can be employed in active accessibility analysis to help to reduce the dependence on private vehicles and promote healthier, more sustainable travel behaviour.

Keywords: Active mobility, Walking, Cycling, Impedance function, Active accessibility, Destination, Temporal, Evolution

1. Introduction

The idea that travel behaviour can be influenced by city form has attracted growing interest in urban and transportation planning. Cities intent to encourage residents to adopt more sustainable modes of transportation, such as walking, cycling, and public transit, by developing environments that offer diverse transportation alternatives while simultaneaously improving accessibility - defined as the of reaching destinations and opportunities (Iacono, Krizek, and El-Geneidy 2008). Active transportation modes, including walking and cycling, play a important role in enhancing and promoting urban sustainability (Hino et al. 2014; Lamiquiz and Lopez-Dominguez 2015), making them central to 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, jointly contributing to the concept of "active accessibility" or "non-motorized accessibility". when incorporated into urban and transportation planning, they help to reduce the dependence on private vehicles and promote healthier, more sustainable travel behaviour among residents.

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There are two main components when measuring accessibility: the location and power of attraction of urban opportunities (trip benefit), and the barrier in travel from the origin 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, since they work 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. In relation to active accessibility, increasing the distance between two points generally implies in a probability decrease of that trip being done by walking or biking (Hansen 1959; Pirie 1979; S. L. Handy and Niemeier 1997; Geurs and Ritsema van Eck 2001; Bhat et al. 2002; Church and Marston 2003; Kwan et al. 2003; 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 situations. In this context, investigate the evolution and dynamics of impedance function over time becomes important, since they are 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 in the province of Vaasa, Finland, attributing this trend to improvements and maturation of the transportation system (Luoma, Mikkonen, and Palomaki 1993). A few years later, Mikkonen and Luoma (1999) argued 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; 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 negative exponential 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 can be 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 captures 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.

Having presented this context, this paper poses the questions: What is the typical travel time for active transportation modes (walking and cycling) in Canadian metropolitan regions, considering various destinations and years? Which impedance functions best represent active transportation travel behavior? To answer the research questions, this study has as two main objectives: first, to provide an overview of the active transportation in terms of main origins, destinations, and travel time; and second, to identify appropriate impedance functions for active transportation modes for different destinations and time periods in Canadian metropolitan areas. To do achieve both objectives, we utilize data provided by the `ActiveCA` R package (Dos Santos, Moghadasi, and Páez, n.d.), 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, the authors extracted all walking and cycling episodes and their corresponding episode weights for GSS cycles, Cycles 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. Our investigation covers a variety of trip purposes, 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 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 the main benefit provided by the transportation system (Pereira, Schwanen, and Banister 2017), being understood as the potential to access spatially distributed opportunities (Hansen 1959; Páez, Scott, and Morency 2012). When computing accessibility measure, is necessary take into account the challenges associated with this access to different locations and opportunities. Usually, the effect of travel costs is expressed by "impedance functions", also called "distance decay functions" (Hansen 1959; Koenig 1980; Fotheringham 1981).

Overall, impedance functions 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). Their main objective is to describe the decrease in the intensity of interaction as the cost of travel between locations increases. The cost of travel is usually 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 fact, 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.

Examining the impedance functions across different modes of transport and destinations is a good way to understand the travel behavior associated with each mode, while also helping to examine allegations about travel behavior. Current interest in creating "livable" communities often relies on broad assumptions about individuals' willingness to walk or bike to different destinations. For example, it is commonly assumed that people are generally willing to walk up to a quarter mile to access most places (Untermann 1984). Similarly, the recent "15-minute city" concept proposes that the majority of daily necessities should be accessible by walking or cycling within 15 minutes (Moreno et al. 2021).

2.1. Impedance functions in accessibility measures

Since the research of Hansen (1959), different categories of accessibility measures have been developed, such as indicators based on actives, infrastructure, individuals and utilities (Geurs and Van Wee 2004; Páez, Scott, and Morency 2012). 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. 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 (Pereira and Herszenhut 2023).

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

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. When Hansen (1959) introduced their accessibility measure, the author applied and indicated the use of exponential distributions ($e^{-\beta x}$) as the impedance function. After this, several other studies (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) (Soukhov and Paez 2024). 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. Usually, c_{min} has value 0.

- **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 gamma 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 and Paez 2024).

- **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 distribution 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 (Dos Santos, Moghadasi, and Páez, n.d.) 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 (Canada 2022). The survey coverage area includes both metropolitan and non-metropolitan regions, ensuring a diverse and representative sample of the Canadian population. Specifically, the seven provinces and three territories 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. One of the standout features of the GSS is its recurring "time use" cycle (Canada 2022), 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.

3. Materials and Methods

To investigate the historical active travel behavior in Canada, we analyzed five GSS Time Use cycles: Cycles 7 (1992), 12 (1998), 19 (2005), 24 (2010), and 29 (2015). We excluded Cycle 2 (1986) from our analysis because this survey did not specify whether the respondent lived in a metropolitan area and did not present cycling as a mode of transportation option, although this cycle is notable for having been the first national random sample to examine Canadian time-use patterns. This paper is a direct application of the ready-to-use data set provided by the `ActiveCA` data package (n.d.), which is based on the Main and Episode files from the GSS Public Use Microdata Files. The Main file contains questionnaire responses and associated data from participants, while the Episode files provided detailed information about every activity episode reported by the respondents. It is important to mention that this study did not analyze the last Time Use survey released (Cycle 37 of 2022, released in June 2024) because, at the time of publication of the study, the Public Use Microdata Files had not been published.

This methodology involves two main steps, each designed to achieve one of our primary objectives. The first step employs descriptive analysis of active transportation episodes to identify typical travel times across destinations and years, comparing their temporal evolution and identifying differences in active transportation episodes through statistical tests. The second step calculates and analyzes impedance functions for each combination of cycle, destination, and active travel mode.

To facilitate collaboration and further analysis, we updated the `ActiveCA` R Package to include the methodology to obtain impedance functions from the raw data files. Additionally, we created this paper using literate programming in which the R markdown code to fully reproduce this article is available on our GitHub repository *(include after the review)*, and we also updated the , in line with the best practices of spatial data science (Arribas-Bel et al. 2021; Páez 2021). These contributions improve our understanding of active travel behaviour in Canada and provide a basis for future research and policy-making.

3.1. Analyzing active travel episodes

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 1992 to 2015. In 1992, there were only three options of origin/destination location available to the respondent: their home, other's home and work or study. In its turn, the most recent survey (2015) counts with twelve possible destination, including sport area (sports centre, field or arena), restaurant (including bar and club), health clinics (medical, dental or other health clinic), grocery stores (including other types of stores and malls) 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 1992 and 1998. For the preceding years (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" "Place of worship," "Grocery store" "Neighbourhood," "Outdoors," "Cultural venues" (such as library, museum and theatre), and "Sport area." This evolution in data collection reflects a growing understanding of the complex nature of urban mobility and the diverse purposes that motivate walking and cycling trips, providing a comprehensive foundation for analyzing distance decay and its implications for urban planning and sustainable transportation strategies.

Statistical analysis was used to characterize active travel episodes using cross-tabulations and graphs. Summary statistics and visualization techniques, including median values as a measure of typical value and boxplots, were employed to describe active travel across years, destinations, and transportation modes. To assess the statistical significance of potential temporal differences in the empirical episode data set for each destination, we applied the Kruskal-Wallis test. This test was chosen because it does not assume a normal distribution for the data, an important consideration since we made no assumptions about the distribution of the empirical data. The identification of impedance functions serves as the step that captures the distributional characteristics of the empirical values. The Kruskal-Wallis test evaluates differences in the medians of the empirical data.

3.2. Analyzing the population with active travel records

After assessing the active travel episodes, we analyzed the population with records of active travel for each year of the analysis. First, we identified the population with and without at least one active travel episode, considering both modes (walking and cycling). After that, for the active population, we examined how active episodes were distributed across the available destinations for each survey year. Finalizing the population analysis, we measured the number of active trips per person for each year, considering both the active and general population.

3.3. Estimating impedance function parameters

We applied the `fitdistrplus` package (Delignette-Muller and Dutang 2015) 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 (17,401 in total), less than 0.7% of the episodes have a trip duration higher than this limit. When considering the weights of this episodes, travel times higher than 100 minutes represented 0.79% of the episodes.

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.

4. Results and discusion

4.1. Descriptive analysis

4.1.1. Walking and cycling episodes

After applying the filters to the GSS surveys, we obtained a total of 12,113 lines with active travel episodes. However, GSS surveys apply a probability sampling methodology, in which each episode or person selected in the sample represents several other episodes or persons not in the sample. The number of episodes and persons represented by a episode or person is determined by the weight or weighting factor. Because of this, every estimates of the number of episodes or persons need to be calculated applying the corresponding weighting factors.

Considering the weights - and from this point onward, all counts estimates presented in this paper account for them - the 12,113 episodes represent a total of 22,731,111 episodes. Table 1 contains the weighted number of episodes about walking and cycling trips between 1992 and 2015, obtained from the GSS cycles. The year 2010 is the year with the most episodes, with 7,116,460 episodes (representing 31.31% of the total). The year 2010 is followed by 2005 with 6,152,778, representing approximately 27.07% of all active travel episodes; followed by 2015 (5,921,772 episodes, 26.05% of the total), 1998 1,773,061 episodes, (7.8% of the total), and 1992, with only 1,767,041 episodes, representing 7.77% of the total.

When analyzing the two active transportation modes, walking episodes account for 91.67%, while the remaining 8.33% are cycling episodes. However, it is worth mentioning that, while in 2015 cycling episodes represented only 8.03% of the active travel episodes for that year, in 1992 the cycling episodes represented 13.03% - the highest share of this mode across all years. In 2005, it drops to the lowest representation level with 7.68%, stabilizing at around 8% thereafter.

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

	1992	1998	2005	2010	2015	Total

Mode		(%)		(%)		(%)		(%)		(%)		(%)
Cycling	230316.9	13.03	156123.1	8.81	472839.5	7.68	559295.6	7.86	475626.6	8.03	1894202	8.33
Walking	1536723.8	86.97	1616937.8	91.19	5679938.1	92.32	6557164.6	92.14	5446144.9	91.97	20836909	91.67
Total	1767040.7	7.77	1773060.9	7.80	6152777.6	27.07	7116460.2	31.31	5921771.5	26.05	22731111	100.00

Tables 2 presents statistic on travel time 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 20 minutes in 1992, dropping to 12 minutes between 1992 to 2005, and increasing again to 13 minutes in 2010 and 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 was 10 minutes in 1992, dropped to 5 minutes in 1998, and remained constant at 10 minutes from 2005 to 2015. The weighted median estimates for walking trips indicates that there is no difference in the typical walking travel time when compared the most recent survey analyzed (2015) with the oldest survey analyzed (1998).

Table 2: Descriptive statistics for episodes with active transport records

		Year				
Mode	Statistic	1992	1998	2005	2010	2015
Walking	Maximum	90	100	100	90	95
	Mean	20	12	12	13	16
	Median	10	5	10	10	10
	Minimum	5	1	1	1	5
	Standard deviation	19	13	12	13	13
Cycling	Maximum	90	80	95	100	90
	Mean	21	28	20	18	24
	Median	20	25	15	10	20
	Minimum	5	2	1	2	5
	Standard deviation	20	19	16	16	15

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 varied a lot, ranging from 18 minutes in 2010 to 28 minutes 1998. In this case, when we analyze the median travel time, we see that the typical cycling travel time fluctuated between 1992 to 2015. It started at 20 minutes for 1992, increased to 25 minutes in 1998 - the highest median travel time identified across all survey cycles - then dropped to 15 minutes in 2005 and to 10 minutes in 2010, before returning to 20 minutes in 2015, the same value as in 1992 when the surveys started. The analysis of travel time statistics alone does not fully explain the reasons behind these fluctuations in travel time over the years. However, it is likely that these variations reflect changes in bicycle technology or cyclist behavior.

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 40%. After that, 'Work or school' appears as the second most common destination, especially for journeys by bicycle, with a peak of almost 36% of trips by bicycle in 1998, a high drop to 23% in 2005, rising again to levels close to 35% 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 almost 10% in 2005 to 5.6% in 2015

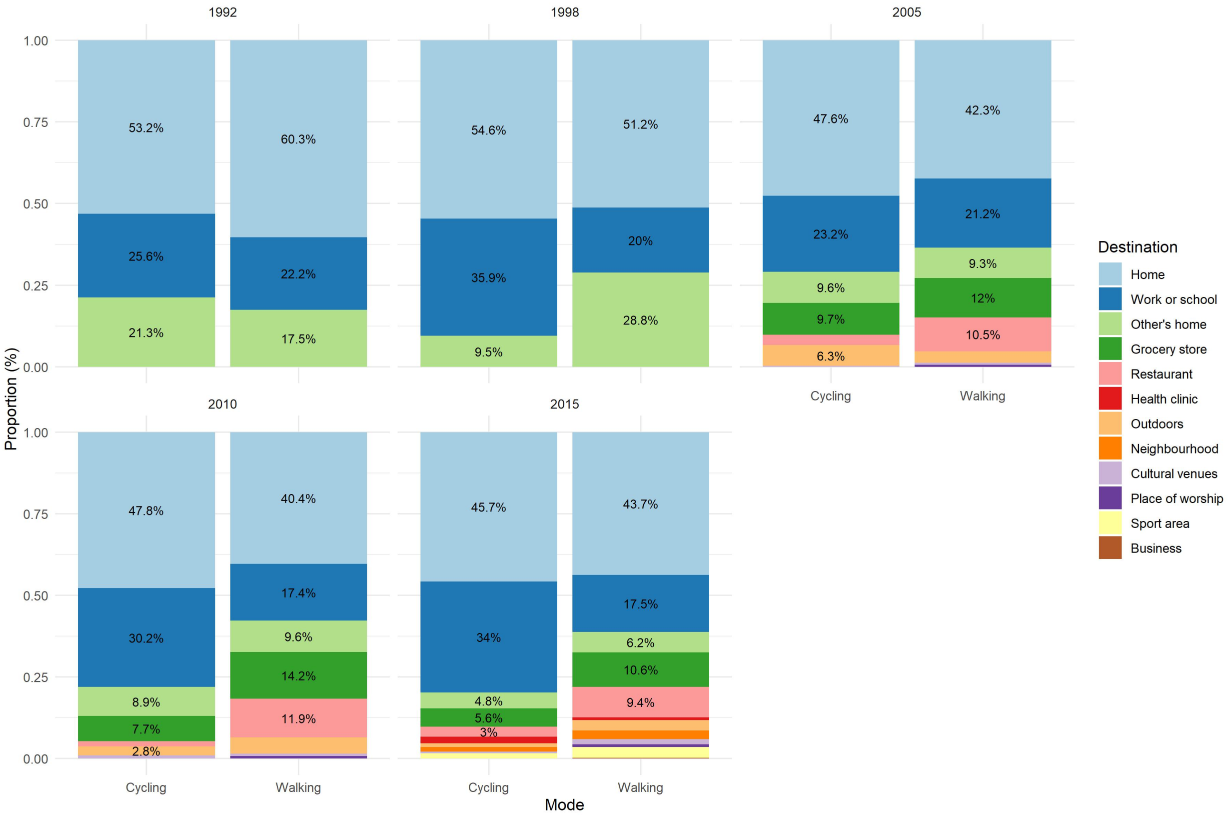

Figure 1: Percentage of walking and cycling trips categorized by destination and year

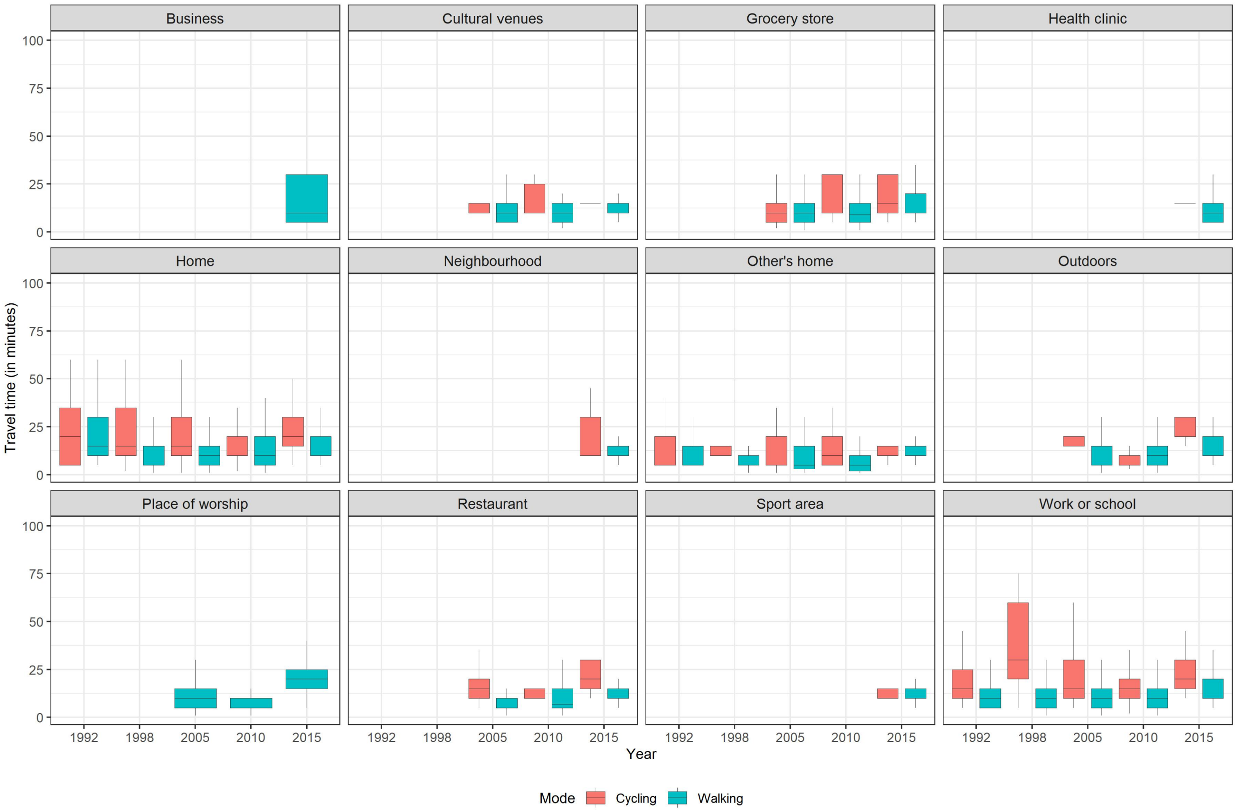

Figure 2: Percentage of walking trips categorized by origin and destination

for cycling trips and from 12% to 10.6% 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. Over the period studied, the typical duration of walking trips was consistently lower than that of cycling trips. Some destinations are presented in only one survey, such as 'Business', 'Health clinic', 'Neighbourhood,' and 'Sport area'. These new destination exhibit typical walking travel times 10 minutes. For cycling trips, 'Business' recorded no trips, and while 'Neighbourhood' registered a typical travel times of 30 minutes, the others cited destinations obtained a typical travel time of 15 minutes.

For destinations included in more than one survey, we can compare the temporal evolution of travel times. Starting with walking trips, we note a trend of increasing travel times for 'Restaurants' and 'Outdoors' (both increasing from 5 minutes in 2005 to 10 minutes in 2015), 'Other's home' (rising to 10 minutes in 2015 after being 5 minutes since 1992), 'Cultural venues' (from 10 minutes in 2005 and 2010 to 15 minutes in 2015), and 'Place of worship' (increasing from 10 minutes in 2005 to 20 minutes in 2015). Other destinations remained constant over time for this active travel mode, such as 'Home', which, after a decline compared to 1992, remained constant at 10 minutes from 2005 onward as the typical travel time. 'Work or school' and 'Grocery store' also remained constant at 10 minutes each since their first appearance in the GSS surveys. In general, while 'Place of worship' displayed the highest median travel time of 20 minutes, the general median walking time cutoff appears to be 10 minutes, with most trips occurring below this limit. In this case, no destination shows a decrease in typical travel (median) time.

For cycling trips, only 'Cultural venues' did not show an increase in typical travel time when comparing 2015 to 2010. In this case, the travel time dropped from 25 minutes in 2010 to 15 minutes in 2015, although it is still higher than the value measured in 2005 (10 minutes). An increasing trend in travel times is evident for destinations such as 'Grocery store' (rising from 10 to 15 minutes between 2005 and 2015) and 'Restaurant' (15 minutes in 2005 and 2010, rising to 20 minutes in 2015). Other destinations seem to follow a similar pattern, where higher travel times were recorded in the earlier survey cycles, dropping over time, and then rising again in the most recent surveys, especially in 2015. This is the case for 'Home,' which returned to the 1992 typical travel time of 20 minutes after dropping to 10 minutes in 2010. It is also worth mentioning 'Work or school,' which had a typical cycling travel time of 15 minutes in 1992, peaked at 30 minutes in 1998, dropped back to 15 minutes in 2005 and 2010, and then increased to 20 minutes in 2015. In this case, no destination shows a decrease in typical (median) travel time. 'Outdoors' presented the longest typical travel time for cycling, reaching a median of 30 minutes in 2015.

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 7% 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 '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.

We analyzed whether the temporal differences in travel times for the destinations had statistical significance. Only destinations that appear in more than one year can have their temporal evolution analyzed. Therefore, from 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 walking trips, it is possible to include 'Place of worship' to the previous destination list.

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 weight of each episode) and the pairwise Wilcoxon test, we were able to identify the destinations where a statistically significant difference was detected. Table 3 shows only the destinations where a statistically significant difference was found, considering the two modes of active transport analyzed.

For both active transportation modes, the possible destinations had at least two year with statistically significant difference in travel times. Considering the cycling mode and, for instance, the "Home" destination, there was a statistically significant difference (p-value $< 2.2\text{e-}16$) for every possible combination of two survey cycles. This result indicates that the previously discussed increase in typical cycling travel time for home destinations when compared 2015 to 2010 is statistically significant. As identified for cycling trips, all destinations presented at least two years with statistically significant difference in travel times for walking trips (p-value $< 2.2\text{e-}16$).

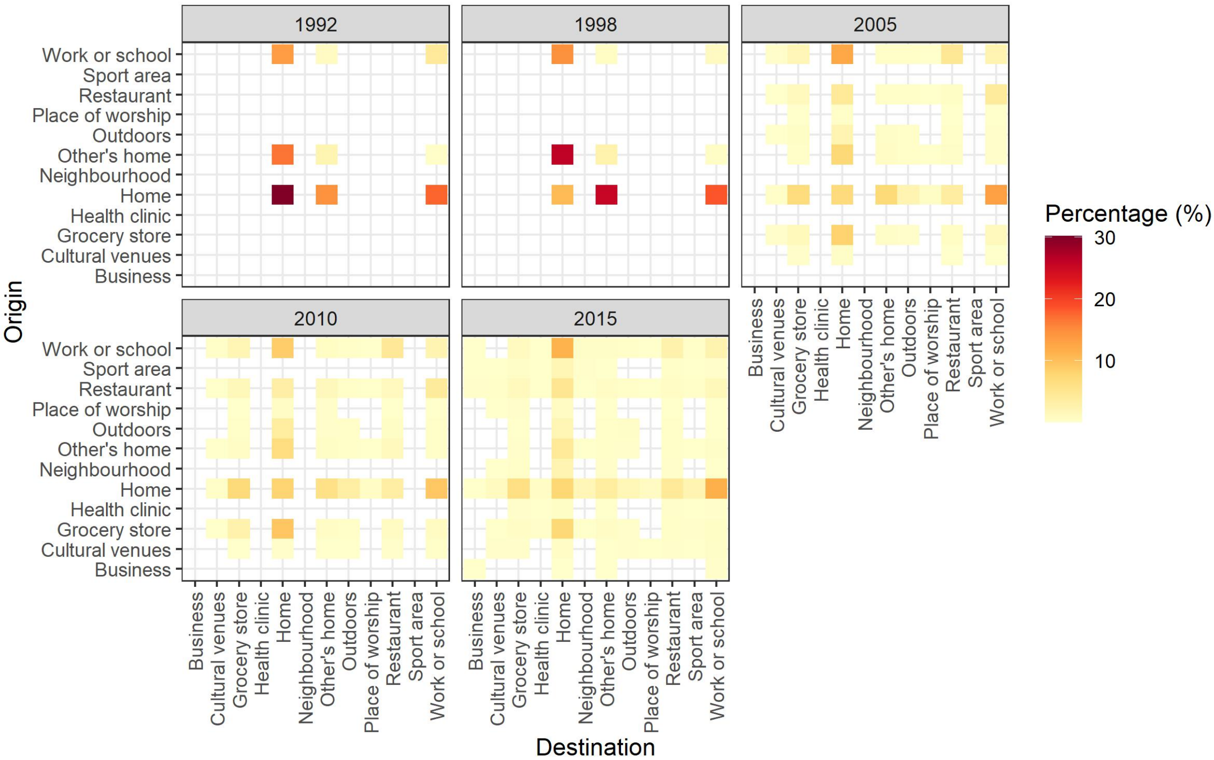

Figure 3: Percentage of walking trips categorized by origin and destination

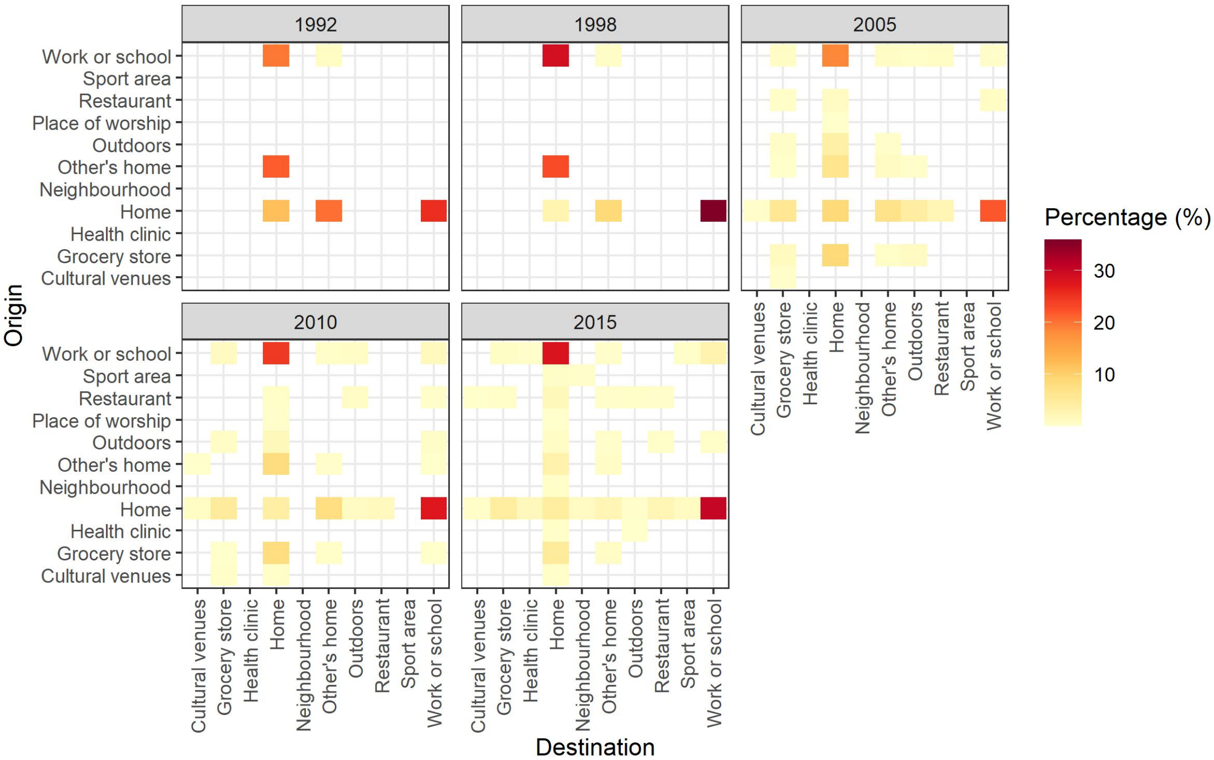

Figure 4: Percentage of walking trips categorized by origin and destination

Table 3: P-values of the pairwise Wilcoxon test .

Mode	Destination	Year	1992	1998	2005	2010
Walking	Restaurant	2010			0	
	Restaurant	2015			0	0
	Grocery store	2010			0	
	Grocery store	2015			0	0
	Home	1998	0			
	Home	2005	0	0		
	Home	2010	0	0	0	
	Home	2015	0	0	0	0
	Work or school	1998	0			
	Work or school	2005	0	0		
	Work or school	2010	0	0	0	
	Work or school	2015	0	0	0	0
	Cultural venues	2010			0	
	Cultural venues	2015			0	0
	Other's home	1998	0			
	Other's home	2005	0	0		
	Other's home	2010	0	0	0	
	Other's home	2015	0	0	0	0
	Place of worship	2010			0	
	Place of worship	2015			0	0
	Outdoors	2010			0	
	Outdoors	2015			0	0
Cycling	Restaurant	2010			0	
	Restaurant	2015			0	0
	Home	1998	0			
	Home	2005	0	0		
	Home	2010	0	0	0	
	Home	2015	0	0	0	0
	Work or school	1998	0			
	Work or school	2005	0	0		
	Work or school	2010	0	0	0	
	Work or school	2015	0	0	0	0
	Other's home	1998	0			
	Other's home	2005	0	0		
	Other's home	2010	0	0	0	
	Other's home	2015	0	0	0	0
	Cultural venues	2010			0	
	Cultural venues	2015			0	
	Outdoors	2010			0	
	Outdoors	2015			0	0
	Grocery store	2010			0	
	Grocery store	2015			0	0

4.1.2. Population with records of active trip

In general, the share of the population with active trip records varied between 7.8% and 14.5% from 1992 to 2015 (Table 4). The year 1998 recorded the lowest level of active trip participation, with 7.8% (1,892,299 people), while 2010 marked the peak of active participation at 14.5% (4,084,114 people). In 2015, the trend of increasing participation in walking or cycling trips, which began after the 1998 low and peaked in 2010, appeared to pause. In that year, the most recent in the analysis, around 11% of the population (3,265,846 people) recorded at least one active trip.

The number of people with active trip episodes is mainly influenced by walking episodes. On average, over 90% of the recorded active trips involve individuals with walking episodes. The percentage patterns for the population with records of walking and cycling trips do not differ significantly from those observed when both modes are considered together.

Table 4: Count and share of population with at least one active travel episode by year

	Walking				Cycling				Total				
Year	Active	(%)	Non-active	(%)	Active	(%)	Non-active	(%)	Active	(%)	Non-active	(%)	Population
1992	1906913	8.96	19387400	91.04	187615	0.88	21106698	99.12	2086672	9.80	19207641	90.20	21294313
1998	1751388	7.22	22508749	92.78	155191	0.64	24104946	99.36	1892299	7.80	22367838	92.20	24260137
2005	3360966	12.88	22734853	87.12	243303	0.93	25852516	99.07	3577772	13.71	22518047	86.29	26095819
2010	3877823	13.81	24197788	86.19	284567	1.01	27791044	98.99	4084114	14.55	23991496	85.45	28075610
2015	3068296	10.31	26698103	89.69	262317	0.88	29504081	99.12	3265846	10.97	26500553	89.03	29766399

Considering only the population with records of walking episodes, Figure 5 shows that, in all the years analyzed, "Home" and "Work or study" were the main destinations (as previously discussed in the previous subsection). On average, those who recorded only one trip accounted for approximately 84% of the population, around 13% recorded more than one walking trip, and the remaining 2 to 3% recorded three or more trips. The maximum number of walking trips registered by a person was 10 episodes (in 1992, 2005, and 2010). In contrast, 2015 shows a reduction compared to previous years, with a maximum of 8 walking trips recorded by a single person. In all these maximum cases, the destination was "Home."

For the cycling population, the maximum number of trips recorded was 4, in 2005 (to "Home" and "Grocery store," as shown in Figure 6). This maximum value is lower compared to the walking population, and there is a higher concentration of cyclists recording only one episode (around 90%), two episodes (around 8%), and the remaining 2–3% recording three or four trips.

Analyzing the number of episodes per person for the general population, the values for each year is very close to 0, ranging from a minimum of 0.009 in 2015 to a maximum of 0.026 in 1992. Considering only the population with active episodes recorded, this value is in average 1.180 active episodes per person, varying from a maximum of 1.203 episodes in 2005 to a minimum of 1.152 episodes per person in 2015. Figure 7 presents these values broken down by mode, walking and cycling. The sum of each category of number of episodes is higher than the population with walking episodes, because some people are counted in more than one category due to different destinations. For instance, a person who went once to the "Grocery store" and twice to "Other's home" will be counted three times.

Since walking episodes form the majority of active trip episodes, the pattern for the walking population is similar to the general trend. For the cycling population, only the low value observed in 1992 for the active population appears different from the overall pattern. However, the number of cyclists in 1992 was not sufficient to alter the overall trend for the active population. These statistics reveal a trend of decreasing active trips per person (whether walking or cycling) when comparing data from 1992 to 2005, with a particularly noticeable decline after 1992 for walking and 2005 for cycling.

4.2. 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

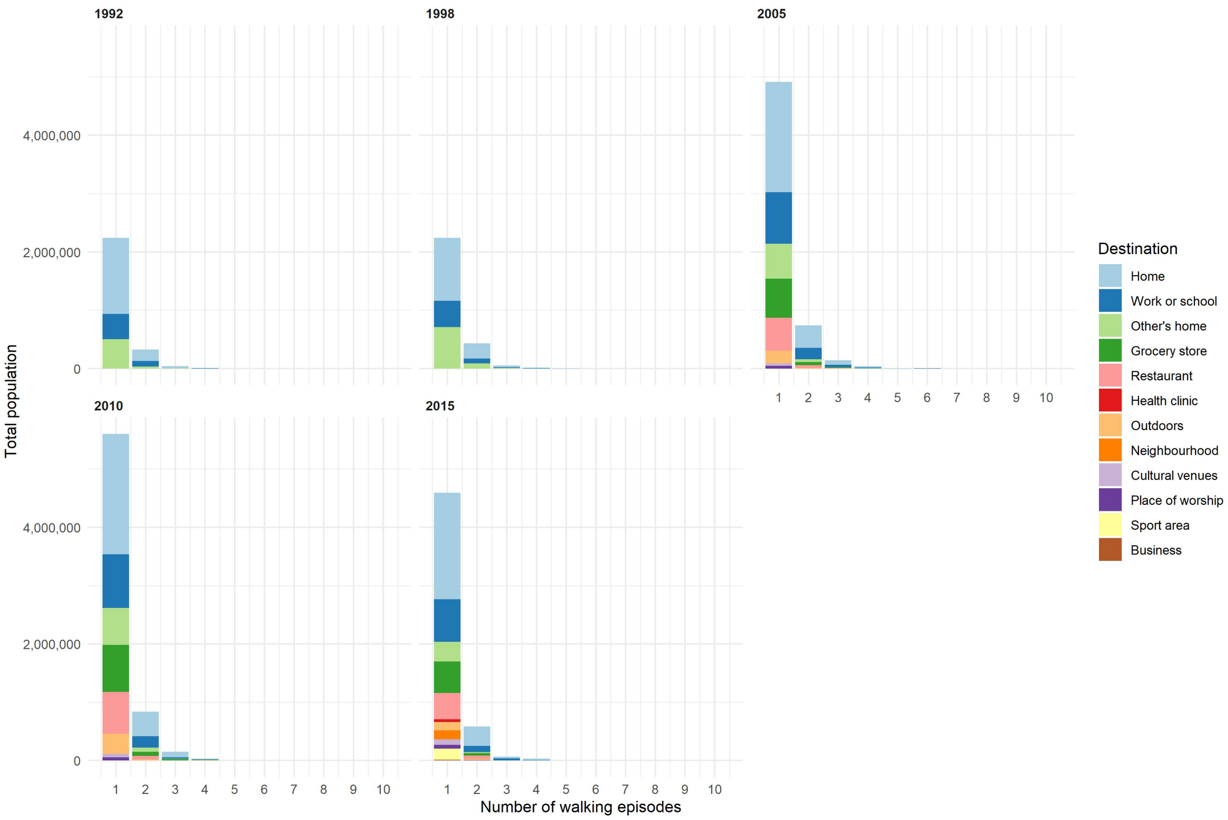

Figure 5: Number of people with at least one walking episodes, by destination and year.

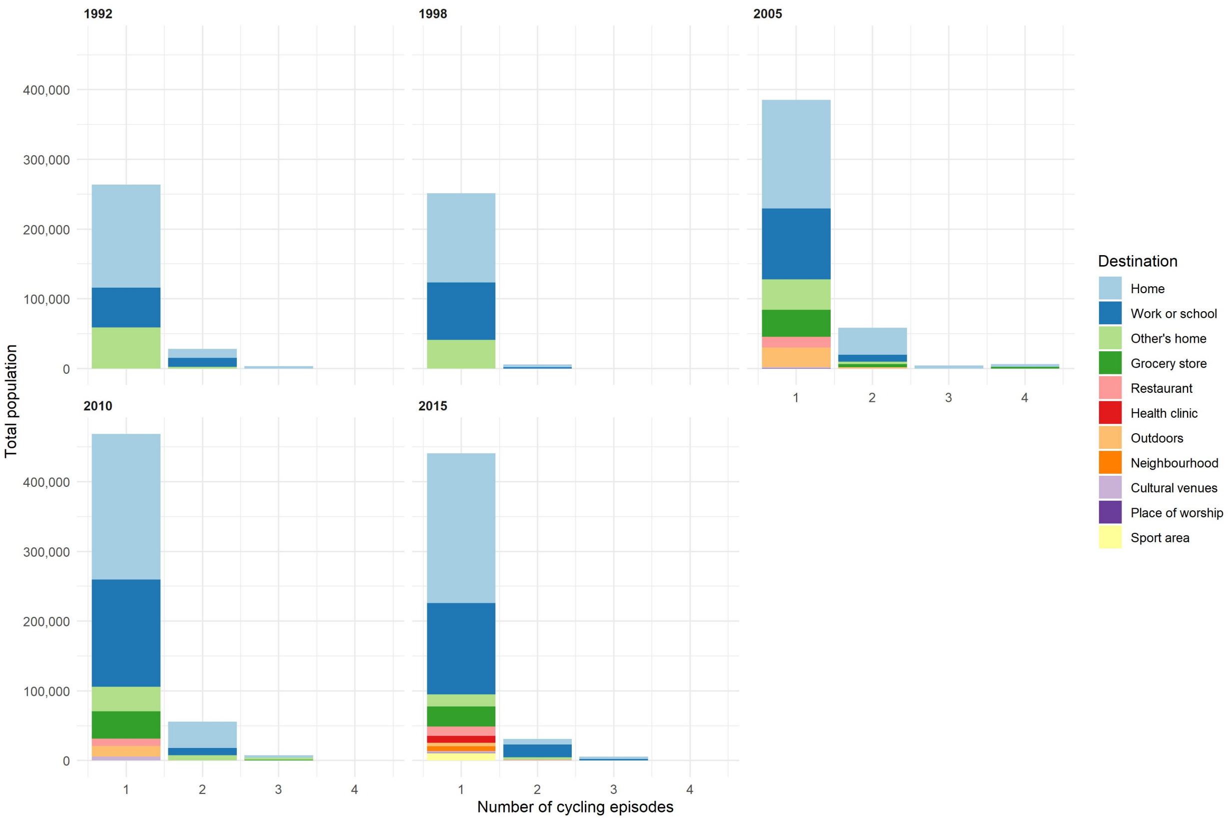

Figure 6: Number of people with at least one cycling episodes, by destination and year.

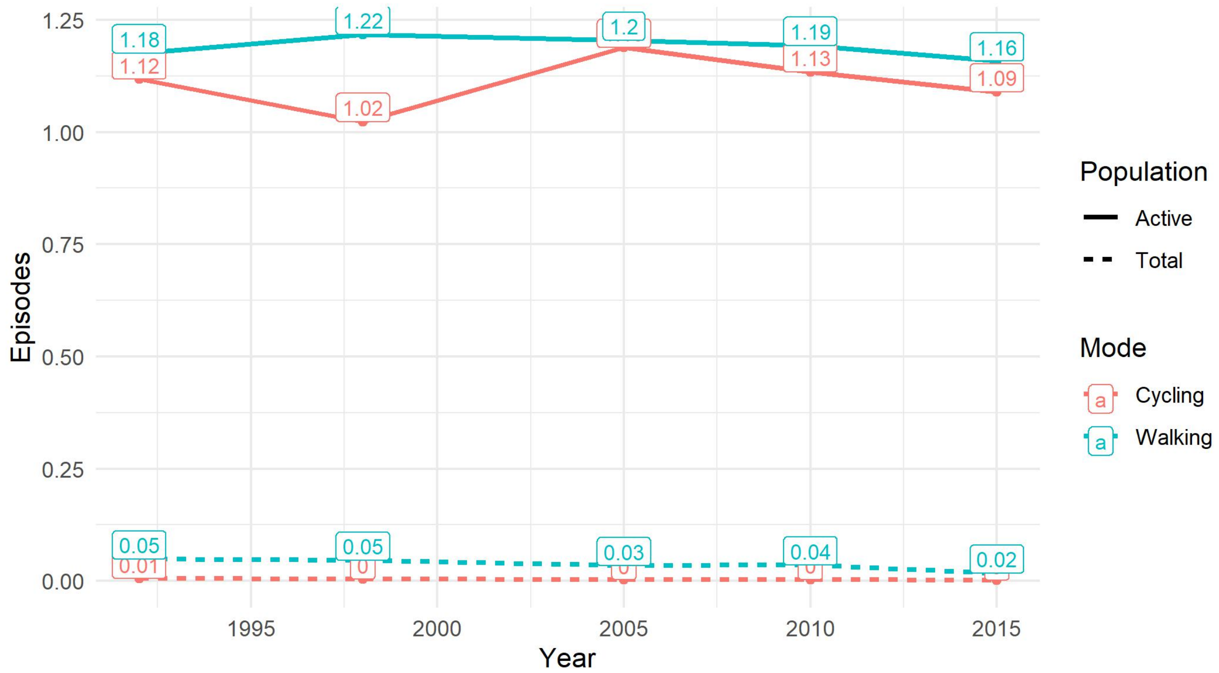

Figure 7: Number of active episodes by person.

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 (Delignette-Muller and Dutang 2015) to calibrate the functions. We selected the best impedance function for each transportation mode, destination, and year based on the lowest Akaike Information Criterion (AIC) value (Akaike 1974). 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, 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 impedance functions applied in active accessibility studies may not be adequately measuring travel behavior, especially for cases when the travel time is close to 0 minute. Table 5 displays the selected functions for walking trips, while Table 6 presents the functions for cycling trips. Appendix A includes the AIC, BIC, and log-likelihood values for all candidate distributions.

Figure 8 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 difficult 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

Table 5: 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
	Other's home	Lognormal	2.15	0.84	1778150	81
	Work or school	Lognormal	2.38	0.70	2319400	113
1998	Home	Lognormal	2.07	0.92	5656275	302
	Other's home	Lognormal	1.75	0.97	2892771	176
	Work or school	Gamma	1.23	0.09	2318752	109
2005	Cultural venues	Gamma	4.10	0.34	238506	25
	Grocery store	Gamma	1.22	0.10	4776215	558
	Home	Gamma	1.16	0.08	17291041	1831
	Other's home	Gamma	1.03	0.11	3420742	436
	Outdoors	Gamma	1.24	0.13	1272012	155
	Place of worship	Gamma	2.07	0.19	228307	32
	Restaurant	Lognormal	1.95	0.79	3727576	421
	Work or school	Lognormal	2.13	0.79	8182691	724
2010	Cultural venues	Gamma	3.60	0.34	304141	25
	Grocery store	Lognormal	2.08	0.85	6369652	489
	Home	Gamma	1.10	0.07	19584386	1424
	Other's home	Lognormal	1.81	0.92	4035574	336
	Outdoors	Gamma	1.27	0.13	2114346	167
	Place of worship	Lognormal	1.95	0.70	285177	28
	Restaurant	Lognormal	2.01	0.90	5187191	371
	Work or school	Lognormal	2.21	0.78	7917431	494
2015	Business	Lognormal	2.41	0.67	102286	8
	Cultural venues	Gamma	4.57	0.34	543242	43
	Grocery store	Lognormal	2.48	0.68	4001111	338
	Health clinic	Lognormal	2.44	0.70	324578	27
	Home	Lognormal	2.57	0.74	17235960	1202
	Neighbourhood	Lognormal	2.41	0.77	981626	53
	Other's home	Lognormal	2.43	0.80	2388598	186
	Outdoors	Lognormal	2.54	0.79	1247963	72
	Place of worship	Gamma	5.64	0.28	343187	24
	Restaurant	Lognormal	2.38	0.74	3490082	231
	Sport area	Lognormal	2.48	0.59	1199687	94
	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 6: 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
	Other's home	Lognormal	2.57	0.82	373451	11
	Work or school	Gamma	3.00	0.17	433582	19
1998	Home	Gamma	1.70	0.07	715802	30
	Other's home	Lognormal	2.79	0.80	113905	7
	Work or school	Gamma	3.37	0.10	481536	19
2005	Cultural venues	Uniform	0.00	15.13	6355	2
	Grocery store	Gamma	1.93	0.14	320218	29
	Home	Gamma	1.49	0.07	1794317	140
	Other's home	Gamma	1.84	0.15	310058	27
	Outdoors	Gamma	2.99	0.17	215894	17
	Restaurant	Gamma	3.37	0.21	109072	10
	Work or school	Lognormal	2.93	0.70	888655	64
2010	Cultural venues	Uniform	0.00	32.58	38938	3
	Grocery store	Lognormal	2.68	0.61	315037	20
	Home	Lognormal	2.60	0.77	2006242	103
	Other's home	Lognormal	2.40	0.63	338777	19
	Outdoors	Lognormal	2.05	0.59	92699	8
	Restaurant	Uniform	0.00	17.49	35370	3
	Work or school	Lognormal	2.65	0.77	1292760	53
2015	Cultural venues	Lognormal	2.71	0.00	-Inf	2
	Grocery store	Lognormal	3.08	0.80	229413	14
	Health clinic	Lognormal	2.93	0.86	80810	4
	Home	Lognormal	3.08	0.61	1745846	98
	Neighbourhood	Uniform	0.00	48.55	49924	3
	Other's home	Lognormal	2.52	0.44	140210	12
	Outdoors	Uniform	0.00	35.03	31463	3
	Restaurant	Lognormal	3.11	0.60	115406	9
	Sport area	Uniform	0.00	17.47	32969	6
	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.

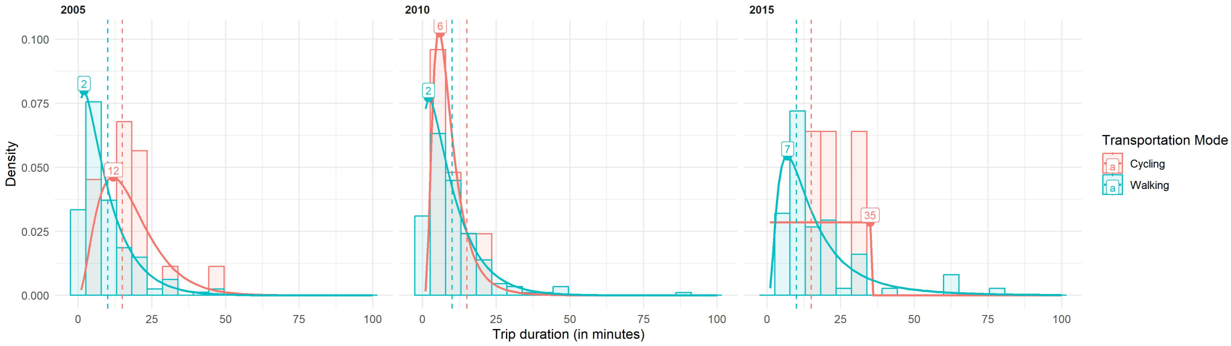

Figure 8: Empirical data and impedance functions fitted for walking trips with ‘work or school‘ as destination.

‘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 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 higher peak and is less dispersed, reinforced by its higher rate (σ).

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 (only 7% of active travel 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.

The complexity of the impedance function will depend of the amount of episodes available to perform the calibration. For instance, to fit a gamma type function was necessary an average of 246 episodes, and to fit a lognormal type function, it was necessary around 187 episodes. In contrast, to fit an uniform function it was required only 3 in average.

The temporal difference between the decay functions is also evident in Figure 9, which shows the calibrated functions for each year of analysis across all destination and transport mode categories for walking

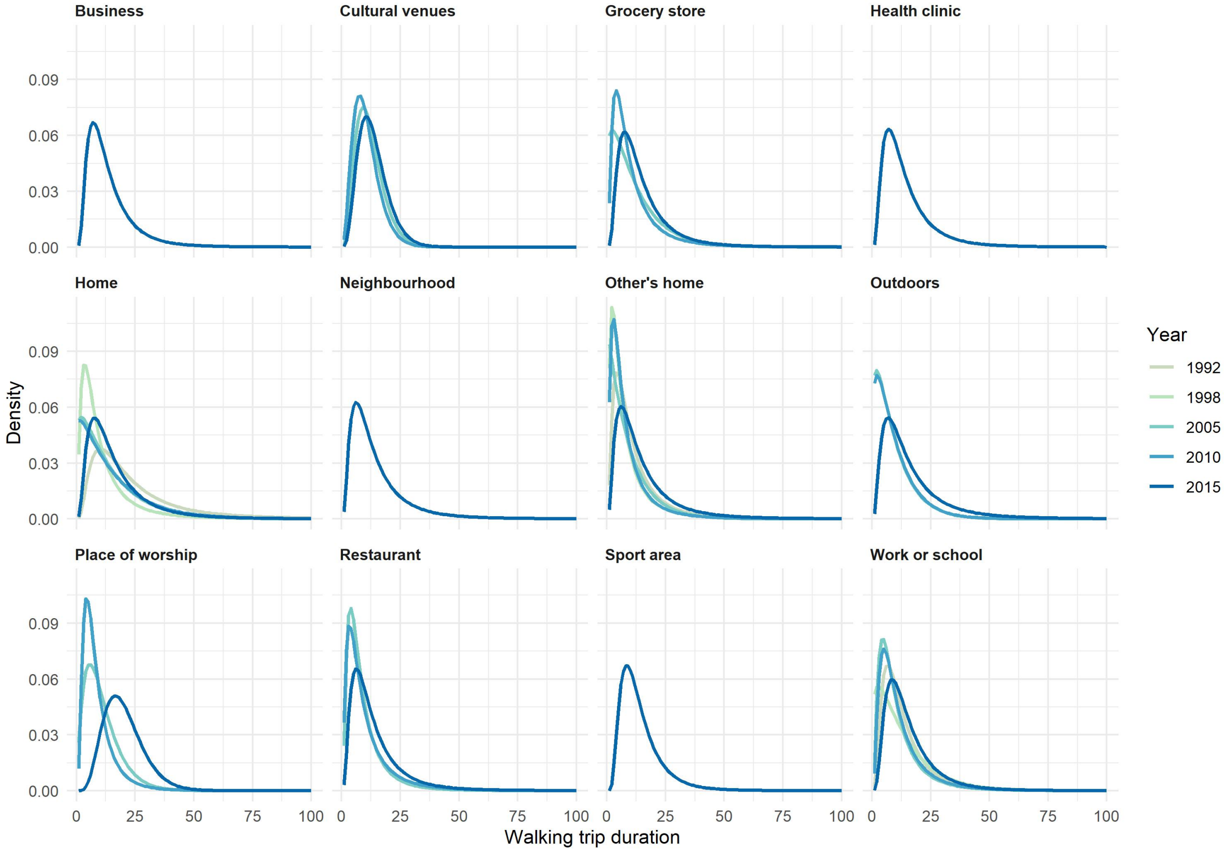

Figure 9: Temporal evolution of walking impedance functions.

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", the only destination present in more than one survey that did not displayed a statistically significant difference for the walking mode, 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.

Finally, Figures 10 and 11 present the impedance functions for different destination categories, grouped by year, for the walking and cycling modes of transport, respectively.

5. Summary and conclusion

The main objectives of this study were to provide an overview of active transportation in Canadian metropolitan cities, focusing on primary origins, destinations, and travel times, and to identify appropriate impedance functions for active transportation modes across various destinations and time periods. In this study we perform a direct application of `ActiveCA` R package (Dos Santos, Moghadasi, and Páez, n.d.), analyzing over 12,000 cases of active travel trips that represented 22,731,111 episodes, from the Time Use cycles of the General Social Survey (GSS) from 1992 to 2015, covering a twelve different type of destinations and considering walking and cycling as transportation modes.

Although the study does not explain the reasons for fluctuations in travel times over the years, the findings confirmed with statistical significance, that typical active travel times remained constant for walking mode, and increased after a dropped since 1998 for cycling mode. For walking trips, typical travel times remained

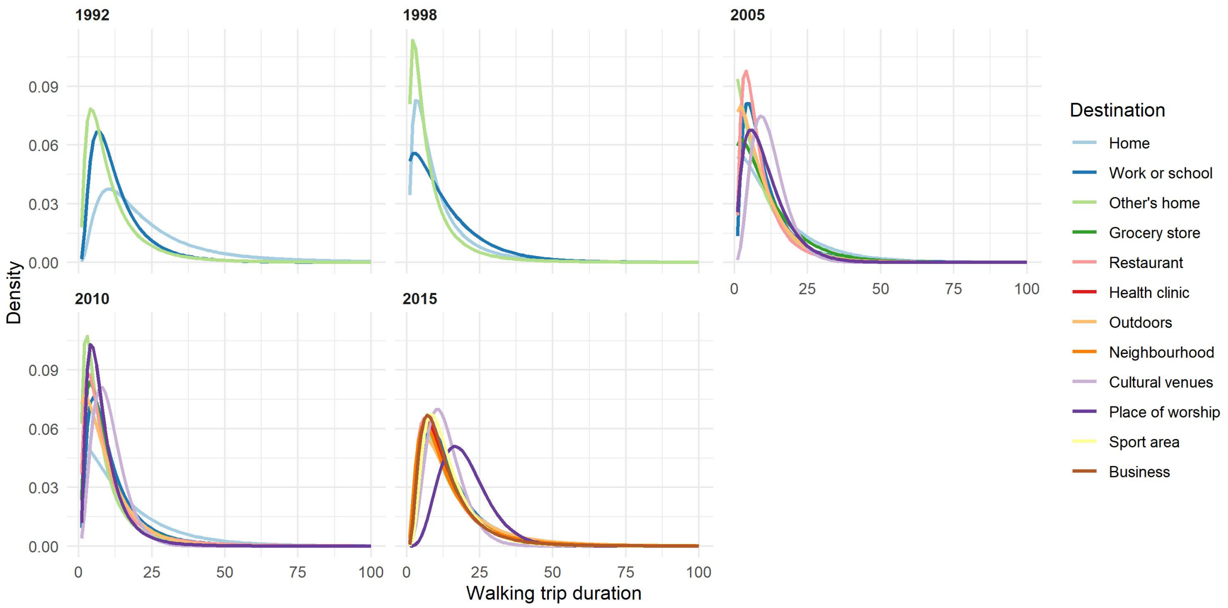

Figure 10: Walking functions grouped by year.

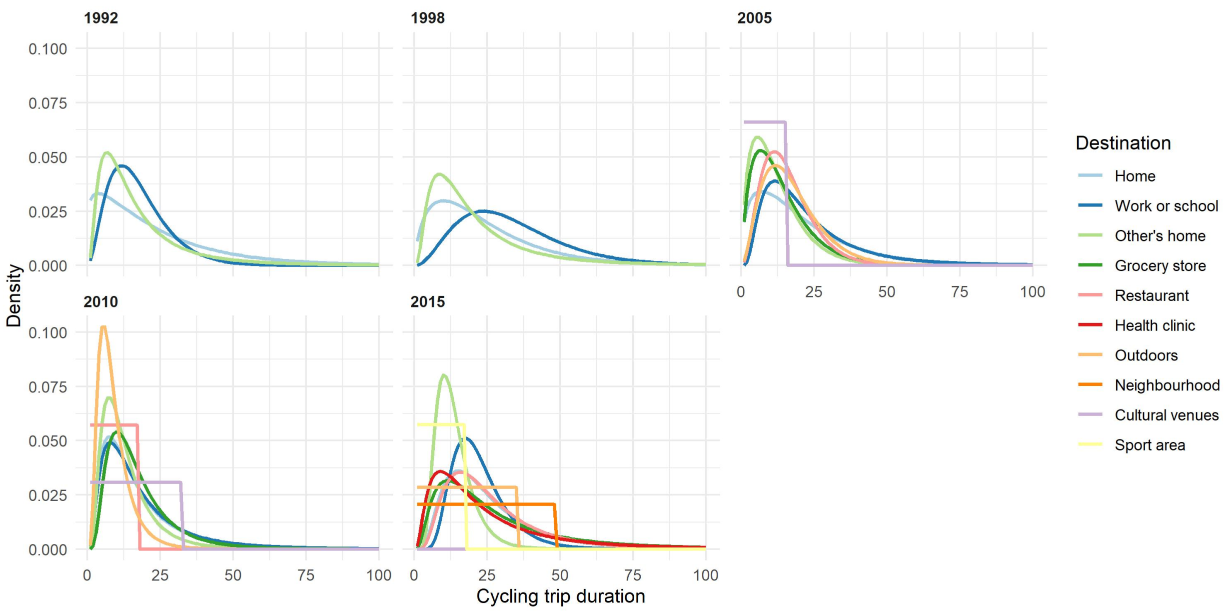

Figure 11: Cycling functions grouped by year.

constant at 10 minutes since 2005. For cycling trips, the typical travel time fluctuated from 20 minutes in 1992 to 25 minutes in 1998, dropped to 15 minutes in 2005, dropped again to 10 minutes in 2010, and returned to increase to 20 minutes in 2015. The results also show that, in general, typical travel times for walking were consistently lower than for cycling.

For walking trips, travel times to 'Restaurants' and 'Outdoors' rose from 5 minutes in 2005 to 10 minutes in 2015, while travel to 'Places of worship' increased from 10 minutes in 2005 to 20 minutes in 2015, marking the highest typical travel time for walking trips. The walking travel time for 'Home' and 'Work or school' remained constant at 10 minutes since at least the three last GSS cycles. For cycling trips, the year of 2015 displayed a trend of increasing travel times for almost all destinations. This trend is perceptible and statistically significant for 'Grocery store' (rising from 10 to 15 minutes between 2005 and 2015), 'Outdoors' (from 15 to 30 minutes during the same period), and 'Restaurant' (from 15 minutes in 2005 to 20 minutes in 2015). 'Home' returned to 20 minutes in 2015 after a drop to 10 minutes in 2010.

For both transportation modes, the destination 'Other's home' showed a decline in the share of trips, reflecting changes in travel behavior since the technological advances enabled people to maintain contact with friends and relatives without visiting in person. For walking trips, findings indicate that 'Home' remains the main hub, whether as an origin or destination. For cycling trips, the combination of 'Home' and 'Work or school' accounted for the largest share of trips.

The population share with at least one active trip record ranged from 7.8% in 1998 (the lowest, 1,892,299 people) to 14.5% in 2010 (the peak, 4,084,114 people). In the most recent GSS survey, from 2015, participation decreased to 11% (3,265,846 people). Walking trips dominate active trips. Approximately 84% of the walking population and 90% of the cycling population recorded only one trip. The maximum number of trips recorded by a person was 10 (in 1992, 2005, and 2010) for the walking population and 4 (in 2005) for the cycling population. The number of active trips per person in the general population was close to 0. Among the active population, this value averaged 1.180 trips per person. A decreasing trend in the number of active episodes per person was detected, whether analyzed in terms of walking or cycling episodes.

The study highlights the need to apply specific impedance functions for different destinations when measuring the cost decay effect in accessibility analyses. Based on this, we fitted 64 impedance functions for active transportation over more than 30 years, considering different types of destinations and transportation modes. The results indicate that none of the parameterized functions were exponential, suggesting that the impedance functions commonly used in active accessibility studies may not accurately capture travel behavior, especially for very short trips (up to 3 minutes), by giving to shorter trips higher probability of being made. Destinations with a high number of episodes were primarily fitted with gamma functions, followed by lognormal functions, while destinations with fewer episodes (fewer than six) were fitted with a uniform distribution.

Given similarities in urbanization processes between Canada, the United States, Australia, and West Europe, these findings may also be applicable to metropolitan areas in those regions. Finally, this study contributes to the ongoing discussion on active transportation, emphasizing its importance in promoting sustainable transportation planning.

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