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

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Abstract

Active transportation (AT), defined as self-powered modes such as walking and cycling, can help individuals meet the Canadian Society for Exercise Physiology's recommendation of 150 minutes of moderate-to-vigorous physical activity per week. Despite the potential of Canada's Time Use Survey (TUS) from the General Social Survey (GSS) to inform AT research, no comprehensive historical analysis of AT using all TUS cycles has yet been conducted. This study addresses that gap with two objectives: to examine temporal trends in AT by destination, travel time, and demographic profiles; and to calibrate impedance functions for AT modes across survey cycles and destinations. After analyzing and processing over 13,500 AT recordins representing 28 million weighted episodes, we performed descriptive analyses and modeled 83 impedance functions. Results show that "Home," "Work or study," and "Grocery store" were the most frequent destinations. Walking dominated AT (over 90% of episodes), with median durations rising from 10 to 15 minutes in 2022; for cycling, durations rose from 15 to 30 minutes. Since 2010, the share of individuals with AT episodes declined, especially among Women+, reversing a previous gender pattern. The group cohort between 15 to 24 years remained as the most active, while adults older than 75 years showed steady increases. All fitted impedance functions deviated from exponential form, indicating that standard assumptions about patterns of distance decay functions may misrepresent AT behavior, particularly for short trips. These findings improve our understanding of active travel trends and provide empirical support for AT accessibility measures and transportation policy.

Keywords: Active mobility, Walking, Cycling, Impedance function, Temporal evolution

1. Introduction

The Canadian Society for Exercise Physiology (CSEP) recommends that adults aged 18 to 64 accumulate at least 150 minutes of moderate-to vigorous-intensity aerobic physical activity per week, in bouts of 10 minutes or more (Canadian Society for Exercise Physiology (CSEP), 2012). Moderate-intensity activities are those that typically cause adults to sweat slightly and breathe harder, such as brisk walking and bicycling. In contrast, vigorous-intensity activities cause individuals to sweat more heavily and become out of breath, including activities like running, basketball, soccer, and cross-country skiing.

The health benefits of achieving the recommended 150 minutes per week (approximately 21 minutes per day) include a reduced risk of premature death (Hakim et al., 1998), heart disease (LaCroix et al., 1996; Hakim et al., 1999), stroke (Hu et al., 2000), high blood pressure (Dunn et al., 1999), certain cancers, type 2 diabetes (Hu et al., 1999), osteoporosis, overweight, and obesity (Fogelholm et al., 2000). Regular physical activity also contributes to improved fitness, strength, and mental health, including better morale and self-esteem (Canadian Society for Exercise Physiology (CSEP), 2012).

Active transportation (AT) is an important source of moderate-to vigorous-intensity physical activity and can help individuals meet recommended activity levels (Bryan and Katzmarzyk, 2009). AT refers

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to non-motorized and self-powered forms of travel, including walking, cycling, and the use of aids such as wheelchairs, scooters, e-bikes, rollerblades, snowshoes, and cross-country skis (Canadian Society for Exercise Physiology (CSEP), 2012). Walking, in particular, is of interest for promoting physical activity among inactive populations because it is low-cost, easily integrated into daily routines, requires no special equipment or training, and carries a relatively low risk of injury compared to more intense physical activities (Hootman et al., 2001; Bryan and Katzmarzyk, 2009). In turn, cycling provides greater health benefits compared to walking, due to the greater intensity and duration associated with this mode (Martin et al., 2014; Barajas and Braun, 2021; Borhani et al., 2024; Celis-Morales et al., 2017).

Both AT modes, 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 (Vandenbulcke et al., 2009; Wu et al., 2019). Walking and cycling accessibility, the ease of reaching destinations and opportunities (Hansen, 1959; Paez et al., 2012) by walking and cycling, are closely related and together contribute to the concept of "active accessibility" or "non-motorized accessibility." When incorporated into urban and transportation planning, they help reduce dependence on private vehicles and promote healthier, more sustainable travel behavior among residents.

In 2021, Canada released the "National Active Transportation Strategy" (Canada, 2021) to support the expansion and enhancement of active transportation infrastructure in Canada. The federal government committed $400 million over five years to build and improve networks of pathways, bike lanes, trails, and pedestrian bridges. Beyond its well-established health benefits, the strategy outlines several additional advantages of expanding AT, including: economic benefits, such as savings on household transportation costs (e.g., fewer vehicle-related expenses, trips, and parking needs), increased tourism and the growth of outdoor and eco-tourism, and increased foot traffic and spending at businesses accessible via AT; environmental benefits, such as improved air quality and environmental resilience due to a higher modal share of AT, reduced land consumption for roads and parking, and decreased water pollution from runoff due to paved surfaces; in addition to social benefits, such as increased public space for social interaction, and improved access to amenities, health care, education, and social services.

In Canada, the Time Use Survey (TUS) cycles of the General Social Survey (GSS), administered by Statistics Canada, offer valuable data for analyzing Canadians' travel behavior (Statistics Canada, 2022). This diary-based survey records individuals' activities over 24 hours to capture societal changes related to living conditions and well-being. TUS cycles have been conducted every five to seven years since 1986. Respondents report their main and simultaneous activities, their duration, location, if other persons accompany them, and, more recently, whether information technology was used during the activity.

The TUS allows researchers to identify the origin and destination of trips, travel times, and transportation modes used, providing a valuable dataset for analyzing active travel behavior. It also offers the empirical foundation for tools used in transportation analysis, such as the development of impedance functions for accessibility analysis.

Despite this potential, to our knowledge, no prior studies have conducted a historical analysis of active travel behavior in Canada using the full set of TUS GSS cycles. Additionally, the lack of calibrated impedance functions, especially for destinations beyond work, poses a challenge for incorporating accessibility into urban and transportation planning (Pereira and Herszenhut, 2023). 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 (Papa and Coppola, 2012; Yang and Diez-Roux, 2012; Millward et al., 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; Geurs and Ritsema van Eck, 2001; Geurs and Van Wee, 2004; Levinson and Krizek, 2005; Cascetta et al., 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. Therefore, 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 et al., 2008, 2010), but also by the transport behaviour of the population.

Given this context, the present study has two main objectives: to investigate the Canadian TUS GSS cycles from 1992 to 2022, offering an overview of AT in terms of primary origins, destinations, travel times, and the demographic profile of individuals engaging in active travel; and to calibrate appropriate impedance functions for AT modes (walking and cycling), considering a wide range of destinations and time periods in Canadian metropolitan areas. To achieve both objectives, we utilize data provided by the `ActiveCA` R package (Dos Santos et al., 2025), 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 TUS GSS cycles. To build this package, the authors extracted all walking and cycling episodes and their corresponding episode weights for GSS cycles, Cycles 2 (1986), Cycles 7 (1992), 12 (1998), 19 (2005), 24 (2010), 29 (2015), and 34 (2022), spanning a period of almost fourty years. Origins and destinations were labelled, 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 advances the current understanding of active travel behavior by analyzing of the evolution of travel times and frequency for AT modes, trends in the prevalence of AT in the Canadian population, and the development of calibrated impedance functions adapted to different destinations, periods and AT modes. We ensured the transparency and reproducibility of our study by sourcing all data from publicly available repositories. To facilitate collaboration and further analysis, we developed this paper using literate programming, with the data analysis code accessible through our GitHub page *(link to be provided after review)*, in alignment with best practices in spatial data science (Arribas-Bel et al., 2021). These contributions enhance the understanding of active transportation, emphasize its role in shaping more sustainable mobility strategies, and provide a foundation for further research and policymaking.

2. Theoretical background

2.1. Evolution of activity transportation in Canada

When analyzing patterns and trends in walking and cycling behavior among Canadian adults on a national scale, two important studies are particularly prominent. The first, conducted by Bryan et al. (2009), examined walking behaviours among Canadian adults aged 18 to 55 using nationally representative cross-sectional data from the National Population Health Survey and the Canadian Community Health Survey spanning from 1994/95 to 2007. The authors calculated the weighted and age-standardized prevalence of walking for exercise, walking duration, regular walking (defined as walking at least four times per week), and whether 100% of leisure-time physical activity energy expenditure (LTPAEE) was derived from walking. Overall, 70% of Canadian adults reported walking for exercise at least once during the previous three months; however, only 30% reported walking regularly - a figure that remained relatively stable since 2001. Regular walking was more commonly reported among women, older adults, individuals with lower body mass index (BMI), and those in lower-income households. Similarly, women, older adults, and lower-income Canadians were more likely to derive 100% of their total LTPAEE from walking compared to men, younger adults, and those in higher-income groups. The study concluded that while walking is a widely practiced form of physical activity across demographic groups, the prevalence of regular walking varies considerably by age, sex, BMI, and income.

The second and more recent study, conducted by Borhani et al. (2024), explored active transportation (AT) patterns in Canada using data from four national health surveys: the National Population Health Survey (1994–1998), the Canadian Community Health Survey (2000–2020), the Canadian Health Measures Survey (2007–2019), and the Health Behaviour in School-aged Children Study (2010–2018). Their analysis assessed the prevalence of AT participation and time spent on active trips, focusing on walking and cycling, with results stratified by age group and sex. The authors noted that inconsistencies in AT survey questions over time and across surveys posed challenges to interpreting long-term trends. Even so, they found that females consistently reported higher levels of walking, while males were more likely to cycle. Regardless of mode, males reported spending more total time in AT. Participation in AT decreased with age, with the highest prevalence observed among youth and the longest durations among young adults.

2.2. The Time Use Surveys in Canada

TUS surveys provide a valuable source of information on the daily activities of individuals and households. According to Harms et al. (2018), more than 65 countries around the world (including in Europe, the Americas, Asia, Africa, Australia, and New Zealand) have conducted together over one hundred TUS. In Canada, the TUS cycles of the GSS have provided a comprehensive cross-sectional snapshot of the Canadian population since 1986 (Statistics Canada, 2022).

Until 2022, Statistics Canada used a telephone-based sampling frame, which was replaced by a dwelling-based frame in the most recent cycle. Most respondents to the 2022 TUS answered the survey online. According to Statistics Canada (2022), this new approach reflected the need to adapt to changes in the use of technology and the increasing time demands of Canadians, offering respondents greater flexibility and convenience in completing the survey. However, it is important to note that significant changes in survey methodology can affect the comparability of data over time. It is not possible to determine with certainty whether, or to what extent, the differences observed in the variables are attributable to actual changes in the population or to methodological changes in data collection. At all stages of processing, verification and dissemination, considerable efforts have been made to produce data with a high level of accuracy and to ensure that the published estimates meet Statistics Canada's quality standards. Even so, there is reason to believe that the use of an electronic questionnaire may have influenced the estimates. The potential impact of the collection mode was analyzed by Statistics Canada for a selected set of key questions. Due to the limitations of the sample size, it was not possible to carry out this analysis for all the variables. It is worth mentioning that none of the variables used in this research are listed in Statistics Canada's 2022 Public Use Microdata File User Guide (Statistics Canada, 2022) as unsuitable for trend analysis due to differences in data collection mode.

Eligibility for participation requires individuals to be 15 years of age or older. Each survey cycle spans a full 12-month period, typically from July to July of the following year. The target population includes all Canadians aged 15 and older, with the exception of residents of the Yukon, Northwest Territories, and Nunavut, full-time residents of institutions, and individuals living on Indigenous reserves. The TUS covers both rural and urban areas, encompassing metropolitan and non-metropolitan regions, thereby ensuring a diverse and representative sample of the Canadian population. For sampling purposes, the ten provinces of Canada were divided into distinct geographic strata. Several Census Metropolitan Areas (CMAs) - including St. John's, Halifax, Saint John, Montreal, Quebec City, Toronto, Ottawa, Hamilton, Winnipeg, Regina, Saskatoon, Calgary, Edmonton, and Vancouver - and some Census Agglomerations (CAs) were treated as separate strata. Additional strata were created by grouping other CMAs within Quebec, Ontario, and British Columbia, as well as by categorizing non-CMA areas within each province into their own distinct strata.

2.3. Impedance functions in accessibility measures

Accessibility is the main benefit provided by the transportation system (Pereira et al., 2017), being understood as the potential to access spatially distributed opportunities (Hansen, 1959; Paez et al., 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" (Soukhov and Paez, 2024). 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 (Li et al., 2020). Their 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.

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 (Richard K. Untermann, 1984; Larsen et al., 2010). 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).

Different categories of accessibility measures have been developed, such as indicators based on actives, infrastructure, individuals and utilities (Geurs and Van Wee, 2004; Paez et al., 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 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 (Soukhov and Paez, 2024).

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, whether for general or specific purposes (Iacono et al., 2008, 2010; Larsen et al., 2010; Yang and Diez-Roux, 2012; Millward et al., 2013; Vale and Pereira, 2017; Li et al., 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 and smooth cost decay functions (e.g., log-normal, normal, gamma, and exponential function) (De Vries et al., 2009; Reggiani et al., 2011; Osth et al., 2016).

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 measure approach. This function determine accessibility by summing up the number of opportunities available within a specific threshold 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 threshold 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 (Hansen, 1959; Apparicio et al., 2008; Iacono et al., 2008; Larsen et al., 2010; Millward et al., 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 et al., 2009; Iacono et al., 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). 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.

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

- **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. 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).

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

- **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. 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.

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

- **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. 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.

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

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.

3. Materials and Methods

To investigate the historical active travel behavior in Canada, we analyzed six GSS Time Use cycles: Cycles 7 (1992), 12 (1998), 19 (2005), 24 (2010), 29 (2015) and 37 (2022). 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 option of transportation mode, 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 (Dos Santos et al., 2025), 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.

The methodology involves two main steps. The first step employs descriptive analysis of AT episodes to identify typical travel times across destinations and years, comparing their temporal evolution and identifying differences in AT episodes through statistical tests, and assess the active population in terms of sex and age group. The second step calculates and analyzes impedance functions for each combination of cycle, destination, and AT 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 (GSS surveys). 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)*, in line with the best practices of spatial data science (Arribas-Bel et al., 2021; Páez, 2021).

3.1. Analyzing active travel episodes

A TA episode refers to a walking or cycling activity that a person did the day before the TUS interview. 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. With this process, 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 CMA 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 2022. 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 (2022) 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, 2015, and 2022 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, 2015, and 2022), 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."

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 box plots, 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 - a test that evaluates differences in the medians of the empirical data. 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.

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, stratifying the analysis by gender and age group. To stratify by gender, we adopted the definition used in the most recent TUS (2022), which was the first in the series to consider gender - recognizing a broader spectrum of gender identities - instead of biological sex, which had previously been limited to female and male categories. In the 2022 survey, due to the small size of the non-binary population, data aggregation was necessary to protect the confidentiality of respondents (Statistics Canada, 2025). As a result, information from the TUS 2022 is disseminated using a two-category gender variable. In this framework, individuals identifying as non-binary are distributed across the two other gender categories and are denoted by the "+" symbol. The category "Men+" includes men (and/or boys) as well as some non-binary persons, and the category women+ includes women (and/or girls) as well as some non-binary persons.

We recognize that biological sex does not always align with gender identity. However, to enable comparison across survey years, we assumed that individuals recorded as "female" in earlier surveys correspond to women+, and those recorded as "male" correspond to "Men+". We acknowledge that this approach does not fully capture gender diversity, particularly for trans and non-binary individuals, due to limitations in how gender was recorded in earlier surveys.

We also stratified the analysis by age group. To ensure the consistency across all survey years, we defined the following cohorts: "15 to 24 years", "25 to 34 years", "35 to 44 years", "45 to 54 years", "55 to 64 years", "65 to 74 years", and "75 years and over".

After defining the gender and age group categories, we identified the population with and without at least one active travel episode, considering both modes (walking and cycling). To complete the population analysis, we measured and examined the temporal evolution of the number of active trips per person for each survey year, considering both the active population and the general population. We also analyzed the number of walking episodes per person who reported walking activity, and the number of cycling episodes per cyclist, to identify possible trends within each AT mode. Finally, we compared the average duration of active travel episodes to observe changes over time.

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

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

	Cycling		Walking		Both modes	
Year		(%)		(%)		(%)
1992	230316.9	13.03	1536724	86.97	1767041	6.30
1998	156123.1	8.81	1616938	91.19	1773061	6.32
2005	472839.5	7.68	5679938	92.32	6152778	21.92
2010	559295.6	7.86	6557165	92.14	7116460	25.36
2015	475626.6	8.03	5446145	91.97	5921772	21.10
2022	474128.9	8.89	4861381	91.11	5335510	19.01
Total	2368330.7	8.44	25698290	91.56	28066620	100.00

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 records (19,166 in total), less than 0.73% of them have a trip duration higher than this limit. When considering the weights of this episodes, travel times higher than 100 minutes represented 0.93% of the episodes. Due to the description of the activities, 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. 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 discussion

4.1. Descriptive analysis

4.1.1. Active transportation episodes

After applying the filters to the GSS surveys, we obtained a total of 19,166 cases of 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 19,166 episodes represent a total of 28,066,620 episodes. Table 1 contains the weighted number of episodes about walking and cycling trips between 1992 and 2022, obtained from the GSS cycles. The year 2010 is the year with the most episodes, with 7,116,460 episodes (representing 25.36% of the total). The year 2010 is followed by 2005 with 6,152,778, representing approximately 21.92% of all active travel episodes; followed by 2015 (5,921,772 episodes, 21.1% of the total), 2022 (5,335,510 episodes, 19.01% of the total), 1998 1,773,061 episodes, (6.32% of the total), and 1992, with only 1,767,041 episodes, representing 6.3% of the total.

When analyzing the two AT modes, walking episodes account for 91.56%, while the remaining 8.44% are cycling episodes. The most recent survey (2022) showed that cycling trips accounted for almost 10% of active travel episodes, reinforcing an increasing trend in the cycling participation since 2005 - the year that marked the lowest representation, as opposed to 1992, when bicycle episodes marked the highest participation in all years (13%).

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

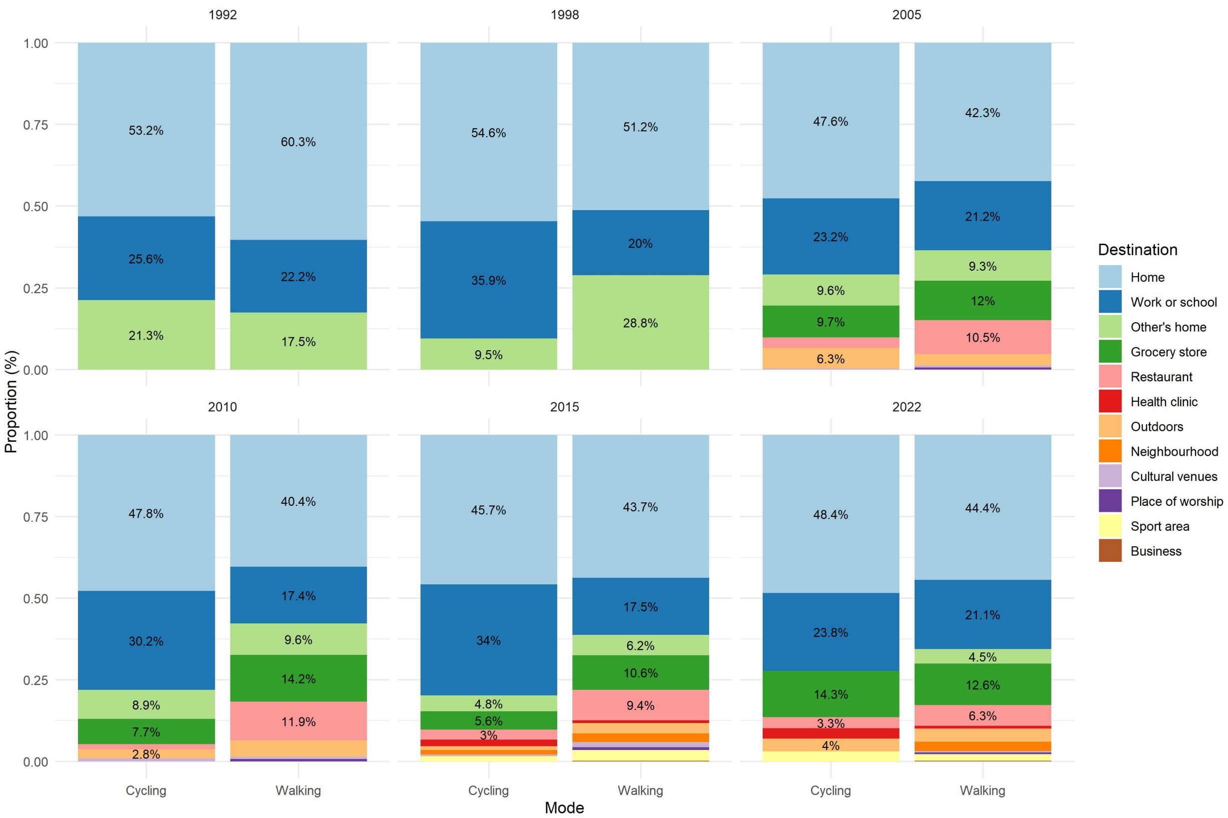

Figure 1: Percentage of walking and cycling trips categorized by destination and year.

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, followed by a high drop to 23% in 2005. 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 does not 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 14.3% in 2022 for cycling trips and from 12% 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.

The maximum time spent on walking trips varied between 90 and 100 minutes across the years (Table 2) - 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, to 16 minutes in 2015, and to 18 minutes in 2022. 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, remained constant at 10 minutes from 2005 to 2015, and increased to the highest level in 2022, to 15 minutes.

Table 2: Descriptive statistics for episodes with active transport records

Mode	Statistic	Year					
		1992	1998	2005	2010	2015	2022
Walking	Maximum	90	100	100	90	95	90
	Mean	20	12	12	13	16	18
	Median	10	5	10	10	10	15
	Minimum	5	1	1	1	5	5
	Standard deviation	19	13	12	13	13	15
Cycling	Maximum	90	80	95	100	90	60
	Mean	21	28	20	18	24	30
	Median	20	25	15	10	20	30
	Minimum	5	2	1	2	5	5
	Standard deviation	20	19	16	16	15	14

For cycling trips, the maximum travel time ranges from 60 to 100 minutes. Until 2022, maximum travel times had a similar pattern to walking trips, but the new survey showed that the maximum travel time for cycling trips was the lowest when considering all years for both modes (walking and cycling). The average cycling travel time varied considerably, ranging from 18 minutes in 2010 to 30 minutes in 2022. When we analyze the median travel time, we see that the typical cycling travel time also fluctuated between the periods, starting at 20 minutes in 1992 and peaking at 30 minutes in 2022. As was also the case with the walking travel times, these results show a trend of increasing for cycling trip duration throughout the years. 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 2 presents box plots showing the distribution of travel times for active transport modes over the years, categorized by destination. During the period studied, the typical duration of walking trips was consistently shorter than that of cycling trips. While we can compare the temporal evolution of travel times, some destinations appear only in the two most recent surveys, such as "Neighborhood," "Health clinic," "Sports area," and "Business." The first three showed a constant median walking travel time of 10 minutes in both surveys, while the median travel time to "Business" increased from 10 to 15 minutes. For cycling trips, "Business" recorded no trips, while "Neighborhood" had a typical travel time of 30 minutes in 2015 but no records for 2022. "Health clinic" showed a constant cycling travel time of 15 minutes, and "Sports area" doubled its typical duration, from 15 to 30 minutes.

For the other destinations, starting with walking trips, we note a trend of increasing travel times for almost all destinations, with an increase observed at least in the most recent survey (2022). "Restaurants" and "Outdoors" both increased their typical travel time from 5 minutes in 2005 to 10 minutes in 2022; "Other's home" rose to 10 minutes in 2022 after remaining at 5 minutes since 1992; "Place of worship" increased from 10 minutes in 2005 to 20 minutes in 2022; and "Cultural venues" rose from 10 minutes in 2005 and 2010 to 20 minutes in 2022. The three most popular types of destinations - "Home," "Work or school," and "Grocery store" - had an increase to 15 minutes after decades of stabilization at 10 minutes. In general, while "Place of worship" and "Cultural venues" displayed the highest median travel times of 20 minutes, the overall median walking time cutoff across all surveys appears to be 10 minutes, with most trips occurring below this threshold. In this case, no destination shows a decrease in typical (median) travel time.

For cycling trips, only "Cultural venues" did not show an increase in typical travel time when comparing 2022 to the previous years. In this case, the travel time dropped from 25 minutes in 2010 to 15 minutes in 2015, although it remained higher than the 2005 value (10 minutes), and no trips were recorded in the most recent survey (2022). "Other's home" is the other destination with no cycling records for the 2022 survey. An increasing trend in travel times is evident for destinations such as "Grocery store" (rising from a median of 10 to 60 minutes between 2005 and 2022) and "Restaurant" (rising to a median of 30 minutes in 2022).

Other destinations seem to follow a similar pattern of increasing travel time, where higher values were recorded in earlier survey cycles, dropped over time, and then rose again in the most recent surveys. This

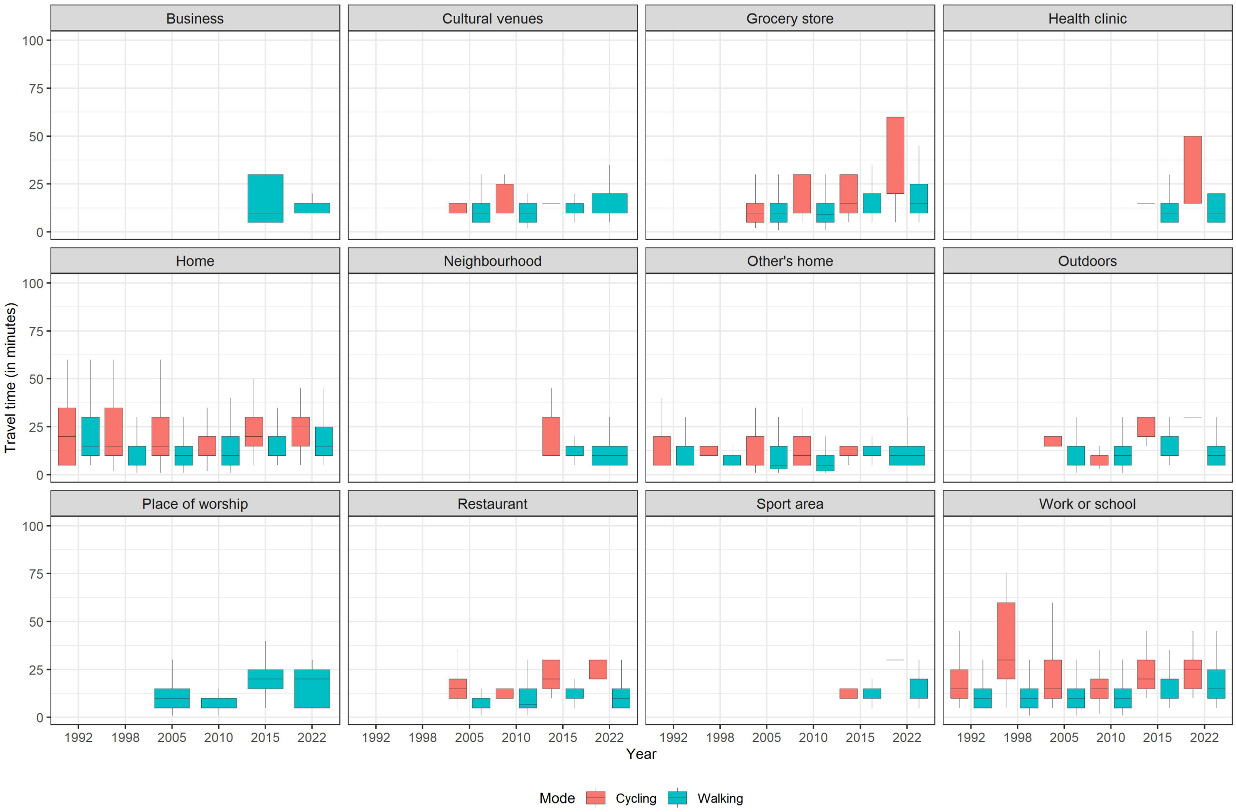

Figure 2: Percentage of walking trips categorized by origin and destination

is the case for "Home," which reached its highest typical travel time of 25 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 25 minutes in 2022. In this case, no destination shows a decrease in typical (median) travel time.

Figures 3 and 4 show walking and cycling trips from 1992 to 2022 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%). 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 the "Grocery store" became a notable destination for trips originating from "Home" (8%) - patterns that were reinforced, as shown in the 2022 survey.~~ In the most recent survey, the most common trip was from "Home" to "Work or school" (17%), followed by the return trip from "Work or school" to "Home" (13%). After that, trips between "Home" and the "Grocery store" accounted for 20% when both directions are combined.

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. However, in 2022, this combination dropped to 43%, mainly due to an increase in trips between the "Grocery store" and "Home" (18%). 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 were statistically significant. Only destinations that appear in more than one survey year can have their temporal evolution analyzed. Therefore, out of the twelve possible destinations, some cycling locations could not be temporally analyzed: "Business," "Neighborhood," and "Place of worship." In the case of walking trips, all destinations could be analyzed over time.

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. For both AT modes, the possible destinations had at least two year with statistically significant difference in travel times (p-value < 0.05, Appendix A). Considering the cycling mode and, for instance, the "Home" destination, there was a statistically significant difference 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 2022 to 1992 is statistically significant.

4.1.2. Population with records of active trip

The share of the population with active trip records varied between 6.93%, value of 1992, and 15.06%, value of 2015, from 1992 to 2022 (Table 3). In 2015, the trend of increasing participation in walking and cycling trips was reversed to the beginning of a decline, confirmed by the 2022 survey. In 2015, around 12% of the population recorded at least one active trip. In 2022, this share of the population fell to 9.45%, the lowest level since 2005, representing *2,605,395* people out of a total population of *27,584,823* people.

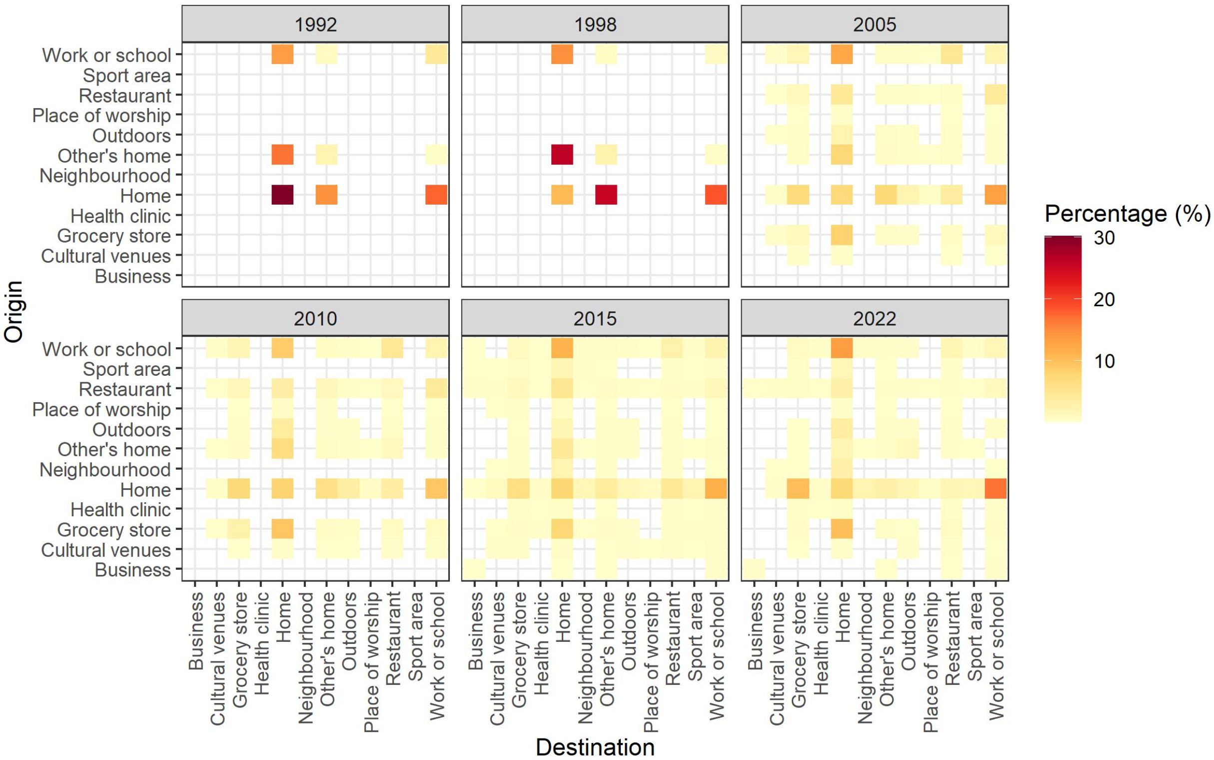

Figure 3: Percentage of walking trips categorized by origin and destination

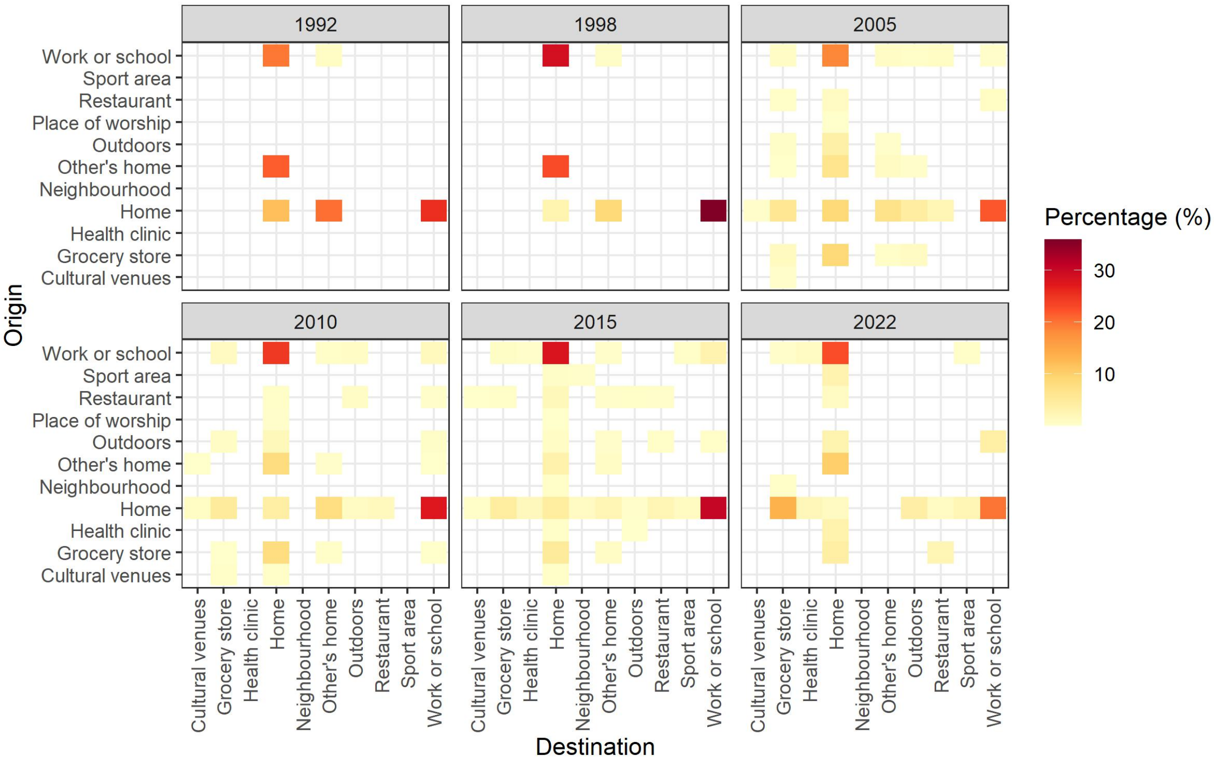

Figure 4: Percentage of walking trips categorized by origin and destination

Table 3: Prevalence of active trip by transportation mode, year of analysis, gender and age group.

	Walking						Cycling						Both modes					
	1992	1998	2005	2010	2015	2022	1992	1998	2005	2010	2015	2022	1992	1998	2005	2010	2015	2022
Total	8.11	6.29	13.18	14.20	10.91	8.66	1.05	0.68	0.99	1.17	0.99	0.89	9.11	6.93	14.06	15.06	11.65	9.45
Men+	7.53	5.03	11.90	13.93	10.85	8.89	1.45	1.18	1.56	1.87	1.34	1.33	8.94	6.18	13.31	15.31	11.89	10.05
Women+	8.69	7.52	14.42	14.46	10.97	8.43	0.66	0.18	0.45	0.50	0.65	0.47	9.27	7.66	14.78	14.82	11.42	8.84
15 - 24	12.48	8.38	25.01	22.28	17.33	19.88	2.50	1.16	2.08	2.75	1.06	1.58	14.97	9.30	26.88	24.01	17.91	21.47
25 - 34	7.15	5.44	13.33	15.24	14.80	9.74	1.66	0.46	1.19	1.17	1.57	1.62	8.82	5.90	14.28	16.11	15.78	11.21
35 - 44	5.79	6.40	10.52	13.46	9.38	5.23	0.65	1.14	1.01	1.06	1.17	0.83	6.24	7.54	11.43	14.34	10.50	5.78
45 - 54	7.55	5.90	9.40	11.69	7.76	5.71	0.30	0.63	0.51	0.84	0.75	0.82	7.73	6.53	9.85	12.35	8.22	6.30
55 - 64	8.89	5.43	9.61	10.91	7.70	5.77	0.25	0.30	0.95	0.86	0.77	0.47	9.14	5.73	10.48	11.75	8.43	6.24
65 - 74	8.55	5.27	8.76	11.59	8.77	6.66	0.00	0.00	0.22	0.42	0.70	0.33	8.55	5.27	8.98	11.82	9.36	6.96
75+	5.92	6.84	13.54	10.91	8.63	6.93	0.00	0.00	0.00	0.07	0.57	0.09	5.92	6.84	13.54	10.98	9.20	7.02

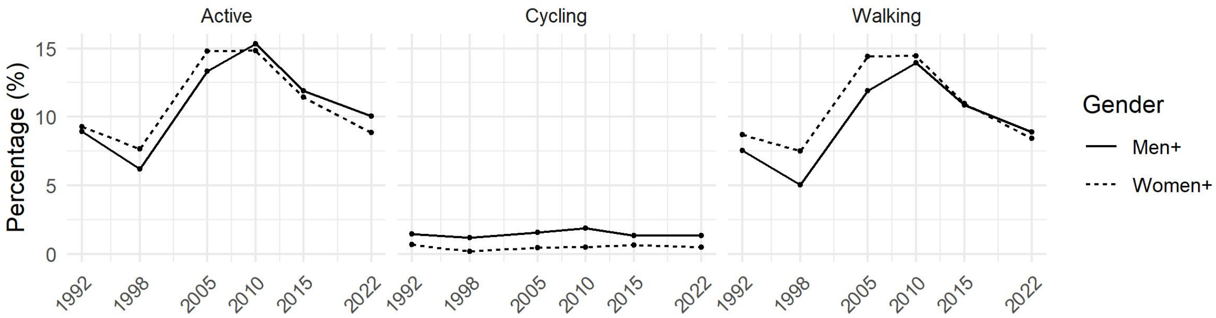

Figure 5: Prevelance in activity transportation by gender.

Our results show a decrease in the active population since 2010 for both genders (Figure 5). However, the decline was more pronounced among women+ than Men+, leading to a shift in the historical pattern in which women+ had been the more active gender in Canada (Bryan and Katzmarzyk, 2009; Borhani et al., 2024). Women+ peaked at 14.82% of the population with a record of active episodes in 2010 but dropped to the second-lowest level of 8.84% in 2022 - only higher than the 7.66% recorded in 1998. In contrast, Men+, who also peaked in 2010 with 15.31% of the population reporting active episodes, declined to 10.05% in 2022, thus becoming the gender with the higher share of the active population.

This result aligns with a trend identified by Borhani et al. (2024). In their study, the authors found that a higher proportion of females than males reported engaging in any form of AT, whether walking or cycling, in the last 7 days or 3 months. However, they also observed that this gender gap appears to have narrowed over time.

When analyzing by transportation mode, in all survey years a higher proportion of men+ reported at least one cycling episode on the previous day compared to women+ (ranging from 1.18% to 1.87% for men+ and 0.18% to 0.66% for Women+). This pattern of more men+ participating in cycling activities when compared to women+ is consistent with previous research (Heesch et al., 2012; Bryan and Katzmarzyk, 2009; Borhani et al., 2024). Conversely, women+ historically reported more walking trips than Men+, also consistent with previous research (Goel et al., 2023; Pollard and Wagnild, 2017; Bryan and Katzmarzyk, 2009; Borhani et al., 2024), but this pattern changed in the most recent survey (2022), reinforcing a trend already present in 2015. In 2022, 8.43% of women+ reported at least one walking episode, compared to 8.89% of Men+.

When we analyze the population by age group (Figure 6), the youngest (those between 15 and 24 years) stand out as the most active group, ranging from 9.3% to 26.88%, and marking 21.47% in the most recent survey. This is the only group that did not show a decrease in the prevalence of active participation over the last decade, increasing from a low of 17.91% in 2015 to 21.47% in 2022 - although still below the levels recorded in 2010 (24.01%) and 2005 (26.88%). The survey of 2022 is one more evidence of caracterists of the Generation z (born between 1997 and 2012) (Dimock, 2019) are noticeably less dependent on cars and instead use environmentally friendly modes of travel, such as public transport, cycling and walking, more often than not (Haseeb and Mitra, 2024; Grimsrud and El-Geneidy, 2014; Kuhnimhof et al., 2011). Historically, and in consistency with the literature (Bryan and Katzmarzyk, 2009; Borhani et al., 2024), prevalence decreases as age increases. However, in the most recent survey (2022), as well as in 2005, the oldest group (75 years and older) presented the third-highest prevalence (7.02%), surpassing the groups aged 35 to 44 years (5.78%), 45 to 54 years (6.30%), 55 to 64 years (6.24%), and 65 to 74 years (6.96%).

The analysis by mode shows a similar trend (Figure 6). However, for cycling, the second youngest group (aged 25 to 34 years) had the highest prevalence in the 2022 survey (1.62%), surpassing the youngest group (1.58%). For all other age groups, cycling prevalence decreases as age increases, approaching 0.10% for the

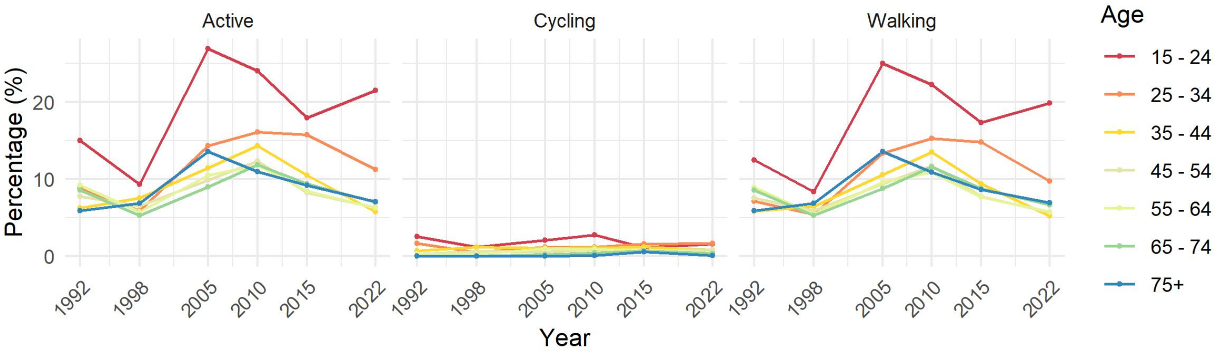

Figure 6: Prevelance in activity transportation by age group.

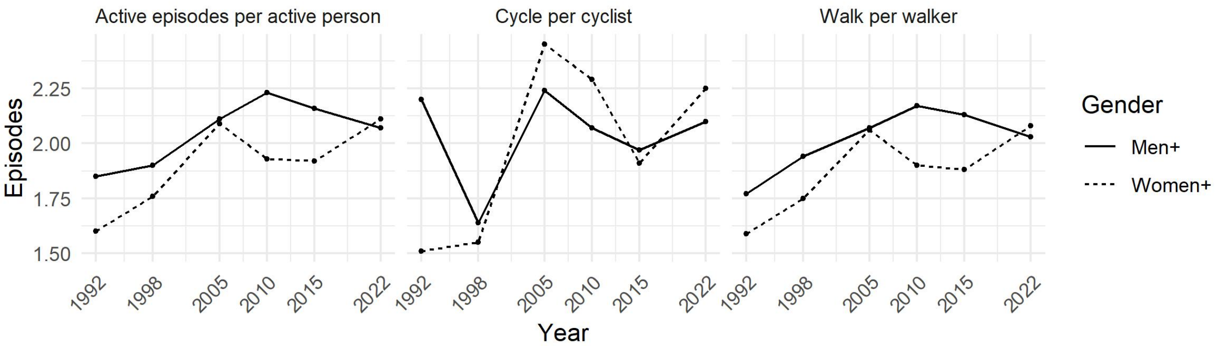

Figure 7: Episodes per active person by gender.

oldest group (75 years and older).

The number of people with active trip episodes is mainly influenced by walking episodes, since over 90% of the recorded active trips involve individuals with walking episodes. Analyzing the number of episodes per person with records of AT, the average is around 1.96 active episodes per person, varying from a maximum of 2.10 episodes in 2005 to a minimum of 1.72 episodes per person in 1992. Figure 7 presents, for each survey year, the total number of active episodes divided by the population with active records, the number of walking episodes per person who walked, and the number of cycling episodes per person who cycled - all disaggregated by gender. Until 2022, men+ historically had more number of active episodes when compared to Women+, but this pattern changed in the last survey when men+ scored 2.07 active episodes, when compared to 2.11 active episodes made by Women+. This was mainly caused by the decreasing of number of walking episodes made by men+ (from 2.16 to 2.07 from 2015 to 2022), and increase of walking episodes made by women+ (from 1.92 to 2.11 in the same period).

The same type of metric shown in Figure 7 can also be calculated by age group. Figure 8 shows that active individuals in the oldest age group (those aged 75 and over) have been on an increasing trend in the number of active episodes since 2010. In 2010, this group ranked last in the number of active episodes per active person (1.94), and by 2022, it had taken first place with 2.21 episodes per active person (a 14% increase). In general, all age groups have improved their performance compared to 1992. However, over a shorter period between the two most recent surveys (2015 and 2022), the group aged 25 to 34 is the only one that showed a decrease in the number of active episodes per active person, decreasing from 2.27 to 1.93 episodes (15% of reduction).

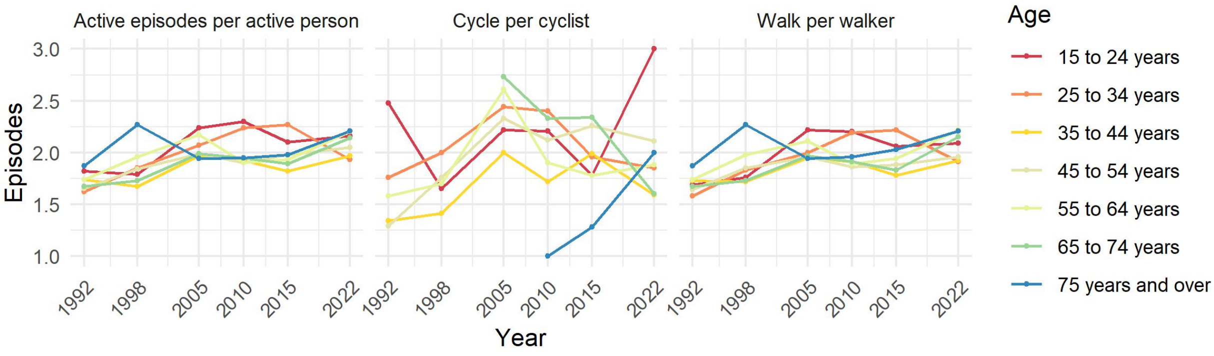

Figure 8: Episodes per active person by age group.

When the age group analysis is split by transportation mode, walking episodes per walker follow a pattern similar to that of total active episodes per active person (Figure 8). However, the pattern for cycling differs. For almost every group, the data can be divided into two distinct time periods: before and after 2005. From 1992 to 2005, there was a general trend of increasing cycling episodes per cyclist (from 1.72 to 2.10). This trend is exemplified by the 55 to 64 age group, which increased from 1.58 to 2.61 episodes (a 65% rise). This period was followed by a decline in cycling episodes per cyclist from 2005 to 2022 (from 2.10 to 2.04). A clear example of this trend is the 65 to 74 age group, which saw a decrease from 2.73 to 1.60 episodes (a reduction of 41%). In more recent years, only two age groups show an increasing trend in cycling episodes per cyclist when comparing the last two surveys (2015 and 2022): the youngest group (15 to 24 years) and the oldest (75 and over). In both cases, there was a significant increase. The youngest group rose from 1.78 to 3.00 episodes (a 40% increase), while the oldest group doubled its average from 1.00 to 2.00 episodes over the seven years.

Regarding the duration of the AT epsiodes, we observe an increase in the average duration of active travel for both genders and both transportation modes after 2010 (Figure 9). When analyzing the typical duration (median) by gender, we find no differences in general active travel. The median remained stable at 10 minutes for both men+ and women+ from 2005 to 2015, increasing to 15 minutes in 2022.

For cycling trips, men+ increased their average duration from 19 minutes in 2010 to 33 minutes in 2022, while women+ went from 15 minutes in 2010 to 22 minutes in 2022 - although this follows a slight decline from a peak of 24 minutes in 2015. This upward trend in travel time contrasts with the period from 1992 to 2010, during which both genders experienced a reduction in duration, reaching their lowest levels in 2010. In this mode, the median cycling duration shows a clear gender difference: men+ reported a median of 30 minutes in 2022, up from 15 minutes in 2005. This represents the highest median duration recorded across the entire historical series. In contrast, women+ tended to maintain a median duration around 15 minutes, which was also the value reported in the most recent survey.

For walking trips, the highest average travel times were recorded in 1992, with men+ averaging 19 minutes and women+ 21 minutes. These values dropped to their lowest point in 1998 (12 minutes for men+ and 11 for Women+) before gradually increasing again through to 2022. Since 2015, women+ have reported longer walking durations than men+ (19 minutes compared to 17 minutes in 2022). Regardless of the mode, men+ reported slightly longer overall active travel durations than women+ in 2022 (19 minutes and 21 seconds vs. 19 minutes and 11 seconds). These results align with findings from previous studies on the Canadian population (Bryan and Katzmarzyk, 2009; Borhani et al., 2024). Again, when we consider the median, the values remained stable at 10 minutes between 2005 and 2015, increasing to 15 minutes in the most recent survey both genders.

An examination of average travel duration by age group reveals a general increase in walking trip durations across all groups since 1998 (Figure 10). In 2022, the youngest cohort (ages 15 to 24) reported the

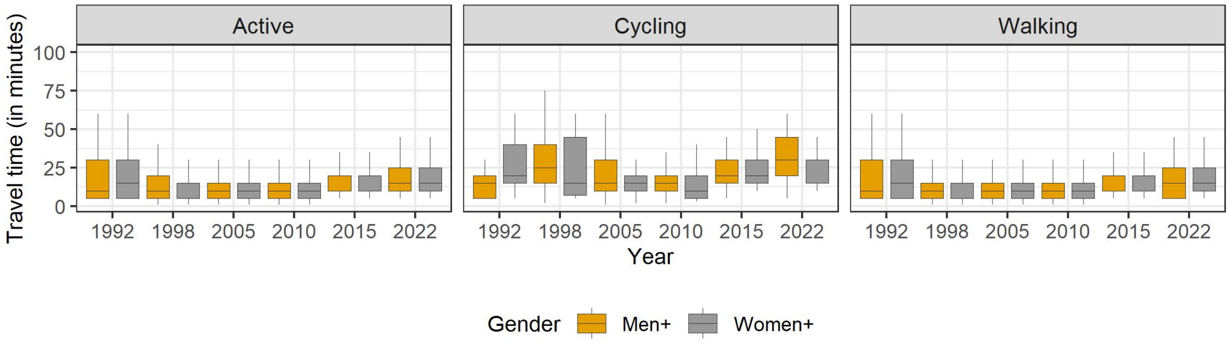

Figure 9: Duration (in minutes) of active episodes by gender.

shortest average walking duration at 17 minutes, while the 25 to 34 age group had the longest, averaging 21 minutes. For cycling trips, a notable increasing trend in duration emerges after 2010 - with the exception of the 55 to 64 age group, whose average duration stabilized following a peak in 2015. Notably, the 65 to 74 age group recorded the highest average cycling duration, with individuals in this cohort spending an average of 42 minutes cycling in 2022.

4.2. Calibrated impedance function

After analyzing the active travel episodes and population with records of active trip, this section presents the identified impedance functions for walking and cycling trips to various destinations across CMA/CA in Canada from 1992 to 2022. 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 (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 83 impedance functions. Among the candidate distributions, only the negative exponential type was not selected. 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 4 displays the selected functions for walking trips, while Table 5 presents the functions for cycling trips.

Figure 11 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 (blue curves), the calibrated functions from this example show a similar pattern. At a duration of around zero minutes, the probability of making the trip is lower (with a density of zero

Figure 10: Duration (in minutes) of active episodes by Age group.

Table 4: 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
2022	Business	Uniform	0.00	20.97	56268	5
	Cultural venues	Gamma	3.89	0.24	157354	12
	Grocery store	Lognormal	2.78	0.62	4618945	192
	Health clinic	Lognormal	2.40	0.98	325649	12
	Home	Lognormal	2.80	0.67	16787347	633
	Neighbourhood	Lognormal	2.28	0.88	963957	33
	Other's home	Lognormal	2.23	0.80	1463414	86
	Outdoors	Lognormal	2.27	0.77	1313257	43
	Place of worship	Uniform	0.00	33.68	160837	11
	Restaurant	Lognormal	2.37	0.70	2098269	100
	Sport area	Lognormal	2.63	0.45	651353	39
	Work or school	Lognormal	2.64	0.63	7432435	192

Note:
For lognormal distributions, 'Parameter 1' and 'Parameter 2' refer to the mean and standard deviation of the distribution on the logarithmic scaler, respectively. For Gamma distributions, 'Parameter 1' and 'Parameter 2' refer to the rate and shape of the distribution, respectively. For uniform distributions, '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 5: 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
2022	Grocery store	Normal	47.03	20.72	602645	8
	Health clinic	Uniform	0.00	61.98	123138	3
	Home	Gamma	4.04	0.15	1798770	56
	Outdoors	Lognormal	3.44	0.11	94804	2
	Restaurant	Normal	26.29	5.83	100585	3
	Sport area	Normal	29.89	17.05	124824	5
	Work or school	Gamma	5.87	0.24	832953	37

Note:
For lognormal distributions, 'Parameter 1' and 'Parameter 2' refer to the mean and standard deviation of the distribution on the logarithmic scaler, respectively. For normal distributions, 'Parameter 1' and 'Parameter 2' refer to the mean and standard deviation of the distribution, respectively. For the gamma distributions, '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.

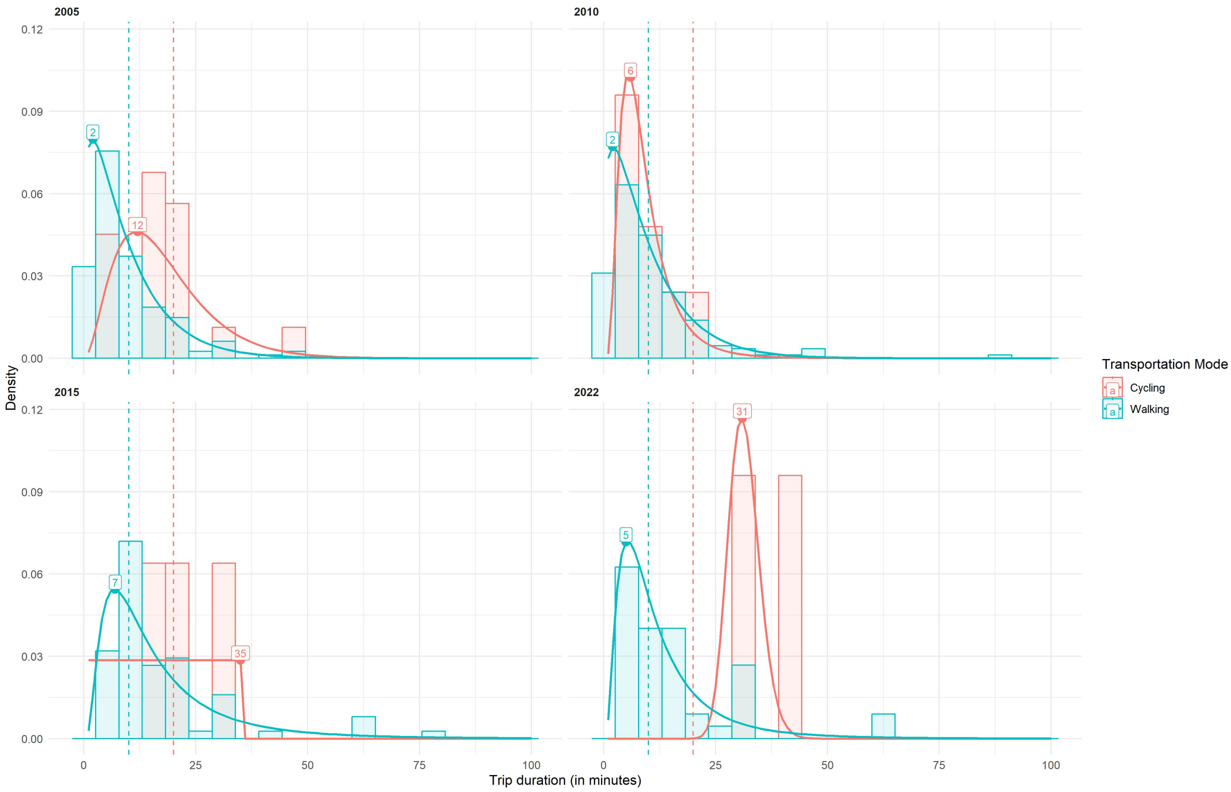

Figure 11: Empirical data and impedance functions fitted for walking trips with 'work or school' as destination.

for the years 2015 and 2022). 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 and 2022, the PDFs that best represent the population's transport behavior are lognormal distributions, with a mean of $\mu = 2.54$ and a standard deviation of $\sigma = 0.79$ for 2015, and a mean of $\mu = 2.27$ and a standard deviation of $\sigma = 0.77$ for 2022. In 2015, the density peak (0.05) occurs at a journey duration of 7 minutes. Here, we observe that a lower density peak corresponds to a more dispersed curve, with higher densities at longer durations. In fact, while in 2005 and 2010 walking trips had densities close to zero for durations over 50 minutes, in 2015 there is still a small density (0.002) at the 50-minute mark. In 2022, the density peak (0.07) occurs at a duration of 5 minutes, and the curve is less dispersed than in 2015, registering lower densities near the 50-minute mark (0.01), in comparison.

For trips made by bicycle, the best-fitting impedance function in 2005 is of the gamma type. For 2010 and 2022, the impedance functions are best represented by lognormal distributions. In 2015, the PDF that best fits the data is a uniform distribution, with an upper bound of 35 minutes and a peak density of 0.028.

The presence of uniform functions means that it was not 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 does not 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 depends on the number of episodes available for calibration. For instance, fitting a gamma-type function required an average of 219 episodes, while fitting a lognormal function required approximately 176 episodes. In contrast, fitting a normal function required only 5 episodes, and fitting a uniform function required, on average, just 4 episodes.

The temporal difference between the decay functions is also evident in Figure 12, 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", consistently uses a gamma function to represent the population's transport behavior for all the years analyzed. In this case, we observe that the average cost is increasing, as the peaks of the PDFs are occurring at longer durations and the curves are shifting to the right. This temporal trend is primarily captured by the σ parameter (rate), which decreased from 4.10 in 2005 to 3.89 in 2022. In contrast, the "Place of worship" destination shows distinct temporal variations, with noticeable changes in peak positions and density dispersion, reflecting the empirical differences observed in Figure 2 and discussed above. The most notable change in this second case is the emergence of a uniform distribution, suggesting that the total number of trips to this destination has declined over time.

5. Summary and conclusion

The main objectives of this study were to provide an overview of AT in Canadian metropolitan cities, focusing on main origins, destinations, travel times and active population on terms of age group and sex, and to identify appropriate impedance functions for AT modes across various destinations and time periods. In this study we perform a direct application of `ActiveCA` R package (Dos Santos et al., 2025), analyzing over 13,500 cases of active travel trips that represented 28,066,620 episodes, from the Time Use cycles of the General Social Survey (GSS) from 1992 to 2022, covering a twelve different type of destinations and considering walking and cycling as transportation modes.

The rate of active trips per person with active record was around two trips, with an increasing trend in active episodes per person being observed for both walking and cycling. Historically, men+ recorded more active episodes than Women+, but in 2022 this trend reversed: men+ averaged 2.07 episodes, while women+ averaged 2.11. This change was driven by a decrease in walking episodes among men+ (from 2.16 in 2015 to 2.07 in 2022) and an increase among women+ (from 1.92 to 2.11 in the same period). In summary, women+ made more active trips, while men+ traveled longer distances and had higher overall participation in AT.

Our results show that the typical duration of walking trips increased to 15 minutes by 2022, following years of stability at 10 minutes. For cycling, the typical duration rose to 30 minutes, recovering from a decline that began in 1998 and lasted until 2010. Generally, walking trips had consistently shorter durations than cycling trips. Although this study does not explain the causes of these fluctuations, the differences by year and mode were statistically significant.

When analyzed by gender, both men+ and women+ experienced increases in trip duration for both walking and cycling after 2010. Men+ increased their average cycling trip duration from 19 minutes in 2010 to 33 minutes in 2022, and median trip duration from 15 to 30 minutes in the same period. Women+ increased their average from 15 to 22 minutes and their median from 10 to 15 minutes. Since 2015, women+ have reported longer walking durations averages than Men+, but when analyzed in terms of median, both presented the same value since 2005, marking 10 minutes until 2015 and 15 minutes in 2022. When analyzing by age groups, all of them increased their active travel times compared to 1992, especially for walking. For cycling, a marked increase in duration emerged after 2010.

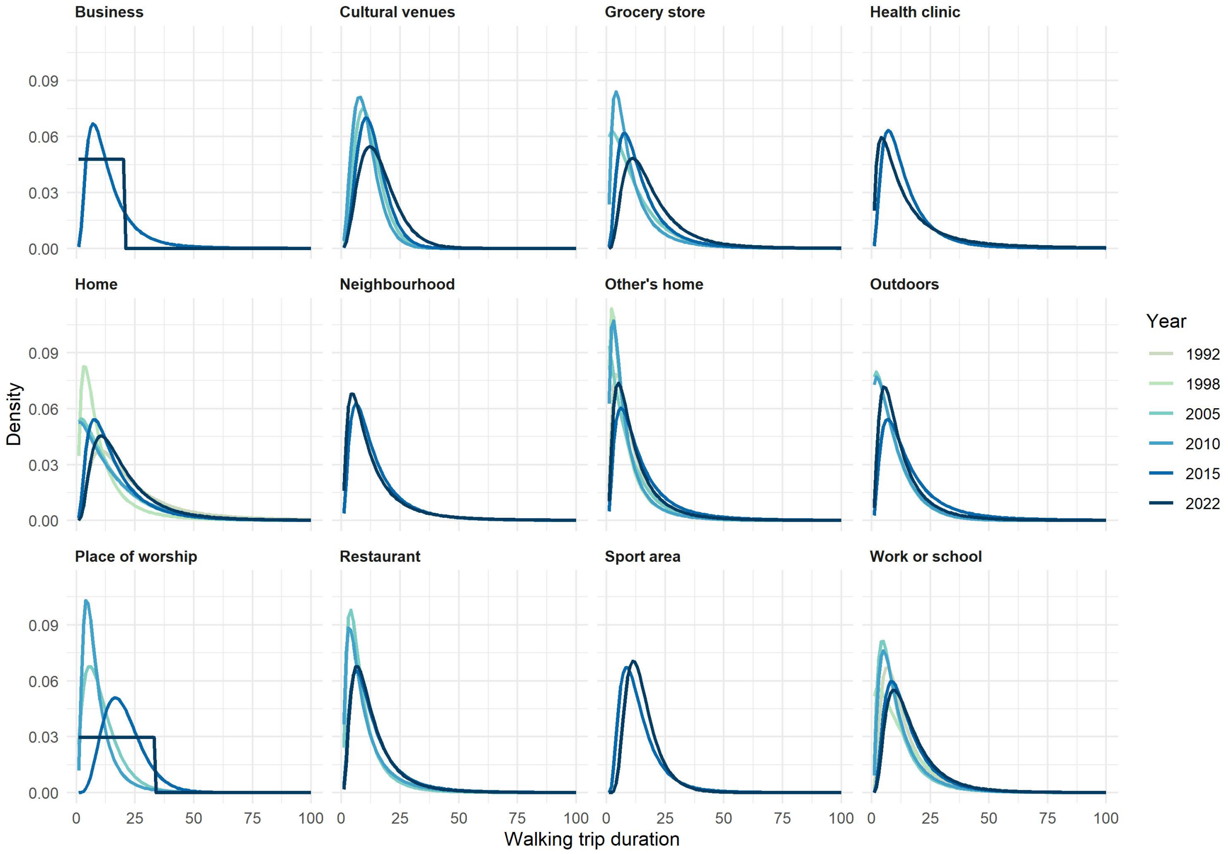

Figure 12: Temporal evolution of walking impedance functions.

For both transportation modes trips to “Other’s home” declined over time, likely reflecting changing social behavior enabled by technology that allows people to stay connected without visiting in person. Walking trips were predominantly associated with “Home” as either the origin or destination. For cycling, the combination of “Home” and “Work or school” accounted for the majority of trips. Walking trip durations to “Restaurants” and “Outdoors” increased from 5 minutes in 2005 to 10 minutes in 2022. Travel to “Places of worship” also rose from 10 minutes in 2005 to 20 minutes in 2022, tying with “Cultural venues” for the highest typical walking travel time. Walking times to “Home” and “Work or school” increased to 15 minutes in 2022, following three GSS cycles where they remained stable at 10 minutes. For cycling, 2015 marked the beginning of a trend toward longer travel times across nearly all destinations.

The share of the population with at least one recorded active trip ranged from a low of 6.93% in 1998 to a peak of 15.06% in 2010. In the most recent GSS survey (2022), participation dropped to 9.45%. Walking dominated active trips, representing over 90% of all episodes.

Since 2010, the active population has declined for both genders, with a steeper decrease among Women+. This reversed a long-standing pattern in which women+ had higher AT participation than Men+. In 2022, men+ showed higher prevalence than women+ regardless of mode, with 10.05% for men+ and 8.84% for Women+. Regarding age cohorts, the youngest group (15 - 24 years) remained the most active, with a prevalence of 21.47% in 2022. This was the only group to show increased participation over the past decade, up from 17.91% in 2015. Generally, AT prevalence decreases with age. However, in both 2005 and 2022, the oldest group (75 years and older) reported the third-highest AT prevalence (7.02%) and showed a steady increase in active episodes since 2010.

The study underscores the importance of applying destination-specific impedance functions when measuring cost decay effects in accessibility analyses. To this end, we fitted 83 impedance functions for AT trips over a 30-year period, considering destination types and transportation modes. The results indicate that none of the fitted functions followed an exponential distribution, suggesting that commonly used functions in AT accessibility studies may not adequately capture actual behavior - especially for very short trips (under 3 minutes), which tend to be overrepresented in these models. Destinations with many episodes were best modeled using gamma functions, followed by lognormal and normal distributions. In contrast, destinations with fewer than six episodes were best represented by uniform distributions.

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 AT, emphasizing its importance in promoting sustainable transportation planning.

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