

# Exploring mobility of care with measures of access: a case for gender-mainstreaming accessibility analysis

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## Abstract

Accessibility, the ease of interacting with opportunities, is an increasingly important tool amongst transport planners aiming to foster equitable and sustainable cities. However, in accessibility research there is a masculinist bias whereby employment destinations are often the default. This paper aims to counter this gendered bias by connecting the Mobility of Care conceptualisation to an empirical accessibility analysis of care destinations in the City of Hamilton, Canada. Care destinations are all the places one must visit to sustain household needs such shopping, errands, and caring for others (children and other dependents). Through the creation of a novel care destination dataset, this paper considers access to care across different modes of transport at two travel time thresholds (trips shorter than 15-minutes and 30-minutes) using unconstrained (cumulative opportunity) and competitive-constrained (spatial availability) measures. Results generally indicate that travel to care destinations by car is exceptionally high, and access by public transit, cycling and by foot is low across the city with some exceptions in the inner city. Notably, there are distinctions between both methods: unconstrained access illustrates a more optimistic landscape for non-car modes, while competitive and constrained access demonstrates a conceptually more realistic spatial distribution of care destination availability. Neighbourhoods with both low spatial availability to care and a high proportion of low-income households are also identified as areas in need of intervention. The manuscript and analysis is computationally reproducible and openly available. The analysis presented demonstrates methods planners can use to gender-mainstream accessibility analysis. Further, results can inform policies aiming to encourage sustainable mobility.

**Keywords:** Accessibility, Mobility of Care, Gender, Cumulative Opportunity, Spatial Availability

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## 1. Introduction

A gender bias exists in transport research and policy (Sánchez de Madariaga, 2013; Law, 1999; Siemiatycki et al., 2020). The field has historically focused on one trip purpose; the on-peak commute to work. While many women do, of course, work, the commute is still a travel pattern more frequent amongst men (Sánchez de Madariaga, 2013). Women, on the other hand, have been found to complete more household-serving travel than men, such as escorting children (Craig and van Tienoven, 2019; Taylor et al., 2015; Han et al., 2019; McDonald, 2006), shopping, and errand trips (Taylor et al., 2015; Root et al., 2000; Sweet and Kanaroglou, 2016).

Though research on the gendered distribution of household-serving travel has existed for decades, it was only in 2013 that Sánchez de Madariaga coined the term Mobility of Care, i.e., all the travel needed to fulfill household needs (e.g., a combination of travel to grocery stores, errands, and pick-up / drop-off of children) (Sánchez de Madariaga, 2013). The term was developed to highlight how these household-serving trips are systematically under-represented, under-counted, and rendered invisible due to masculinist biases in transport planning. Take, for instance, how trips to household sustaining destinations are categorized in typical large-scale travel surveys (Sánchez de Madariaga, 2013). In the Greater Golden Horseshoe Area’s (encompassing the Greater Toronto and Hamilton Area) Transportation Tomorrow Survey (TTS) (Data Management Group, 2018a) respondents are given the following options to categorize their trip origins and destinations: home, work, school, daycare, facilitate passenger, marketing/shopping, other, or unknown. While home-work and home-school trips are easily identified, care trips are more challenging to measure. Many marketing/shopping trips are likely for care purposes (e.g., groceries), but others are likely for leisure. While escort trips are likely well captured under the categories ‘daycare’ or ‘facilitate passenger’, trips to run errands or to attend health appointments are not clearly captured. It is probable that respondents categorize many of these trips as ‘other’ or even ‘unknown’. The focus of the survey is on what is a ‘typical’ trip to work or school (Data Management Group, 2018a); other trips are a by-product, ‘non-typical’ and minimialised in importance. Of course, people’s travel behaviours are complex and surveys must balance detail with summary. However, what is seen as a ‘typical’ trip continues to shape transport and land-use, and this aggregation steers data-driven solutions from counted and observed home -work/-school based trips.

When travel surveys are designed to explicitly capture mobility of care, preliminary research has found that it comprises approximately one third of adults’ trips (Gómez-Varo et al., 2023; Sánchez de Madariaga, 2013; Sánchez de Madariaga and Zucchini, 2019; Ravensbergen et al., 2022). Given the large proportion of

daily travel that mobility of care comprises, these trips should be explicitly captured in transport research. Further, the current under-reporting of mobility of care in research and planning has important equity considerations. Not only are mobility of care trips completed predominantly by women, this gendered discrepancy is greater in low-income households (Murillo-Munar et al., 2023; Sánchez de Madariaga, 2013; Ravensbergen et al., 2022). For instance, in lower income households in Montréal, women complete 50% more care trips than men (Ravensbergen et al., 2022).

The power of the Mobility of Care concept lies in its ability to highlight the masculinist bias in transport research – travel for care appears insignificant because travel surveys are not written to capture it (Sánchez de Madariaga, 2013). Travel surveys, however, are but one tool used by transport researchers and practitioners. Another popular tool in transport planning and research is accessibility, an indicator that quantifies “the potential of opportunities for interaction” as defined in the seminal work of Hansen (Hansen, 1959). Accessibility indicators can be interpreted as the ease of reaching destinations using transport networks: a byproduct of mobility and a representation of the people’s interaction with land-use and transportation systems (Hansen, 1959; Handy, 2020; El-Geneidy and Levinson, 2021). The points of interest in many accessibility-based assessments have been home-to-work destinations (Kelobonye et al., 2019; Farber and Allen, 2019; Duarte et al., 2023; Ryan et al., 2023). For example, in the accessibility assessment of the Ontario Line, a subway line that will be constructed in the city of Toronto, Canada, Farber and Allen (Farber and Allen, 2019) highlight how this new investment will increase access to jobs for residents across the City by 1.14% overall. While much has been learned, shifting focus from jobs as the default destination may open opportunities for gender-mainstreaming accessibility analyses. Indeed, jobs are not always the most significant destination for many segments of the population. As discussed, women’s commutes comprise on average a smaller proportion of their daily travel than men’s (Ravensbergen et al., 2022). This focus on job-access can additionally bias accessibility-gains that children and older adults who reside in impacted areas may see as well (Grant-Smith et al., 2016). One way to counter this bias is to reframe accessibility analysis by explicitly considering destinations involved in mobility of care.

Reframing accessibility analyses to incorporate mobility of care is also pertinent to the promotion of sustainable travel modes in cities. Research has found that people are less likely to use public transport or bicycles for care trips (Ravensbergen et al., 2022) and more likely to make these trips by car (Maciejewska and Miralles-Guasch, 2019; Ravensbergen et al., 2022). A lack of access to care destinations by bicycle and transit may contribute to these trends. Mobility of care is also more commonly completed by foot than the

commute to work ([Ravensbergen et al., 2022](#)). Whether there is a relationship between these travel behaviors and people’s access to care destination using different modes, however, remains unknown, as mobility of care is largely uncoun-  
ted in transport research.

In this spirit, this study foregrounds the theoretical mobility of care concept by calculating the accessibility to care destinations or multiple modes in an empirical case study of Hamilton, Canada. Two place-based accessibility measures are used to motivate the discussion: one unconstrained measure (cumulative opportunity) and another competitive and constrained measure (spatial availability ([Soukhov et al., 2023](#))). The cumulative opportunity measure demonstrates the potential access to all destinations within 15-minutes and 30-minutes. This measure is widely appreciated for its intuitive computation ([Handy, 2020](#); [Handy and Niemeier, 1997](#); [Kelobonye et al., 2019](#); [Cheng et al., 2019](#)) but critiqued for its omission of competition effects ([Paez et al., 2019](#); [Soukhov et al., 2023](#); [Kelobonye et al., 2020](#); [Merlin and Hu, 2017](#)). To respond to this critic, spatial availability of care destinations per mode is also calculated as an additional and arguably more conceptually realistic reflection of opportunity availability. This research aims to contribute to gender-mainstreaming in transport planning by demonstrating an approach to a feminist accessibility calculation through these two accessibility measures.

## 2. Background and methods

This paper focuses on Hamilton, a mid-size city of approximately 500,000 residents that lies within the urban and suburban Greater Toronto and Hamilton Area (GTHA) ([Data Management Group, 2018a](#)). The GTHA is home to seven million people, or approximately 20% of the Canadian population ([Toronto, 2022](#)). Hamilton is divided into six regional communities (Figure 1). Hamilton-Central is the densest and most urbanized of the six, and the five periphery communities of Dundas, Ancaster, Flamborough, Glanbrook and Stoney Creek are significantly more suburbanized with the furthest periphery regions being undeveloped or rural owing to their inclusion in the region’s greenbelt ([Greenbelt Foundation, 2023](#)). These different urban forms and associated transport infrastructure play a key role in access to care destinations.

Further, the entire manuscript and all analysis is conducted in R and RStudio. All work is computationally reproducible and openly available in the lead author’s [GitHub repository](#).

### 2.1. Destination dataset

A geospatial dataset of care destinations for Hamilton (e.g., full addresses of longitude and latitude) was compiled. The geospatial data was sourced from provincial and municipal open data portals ([Ontario, 2023](#);

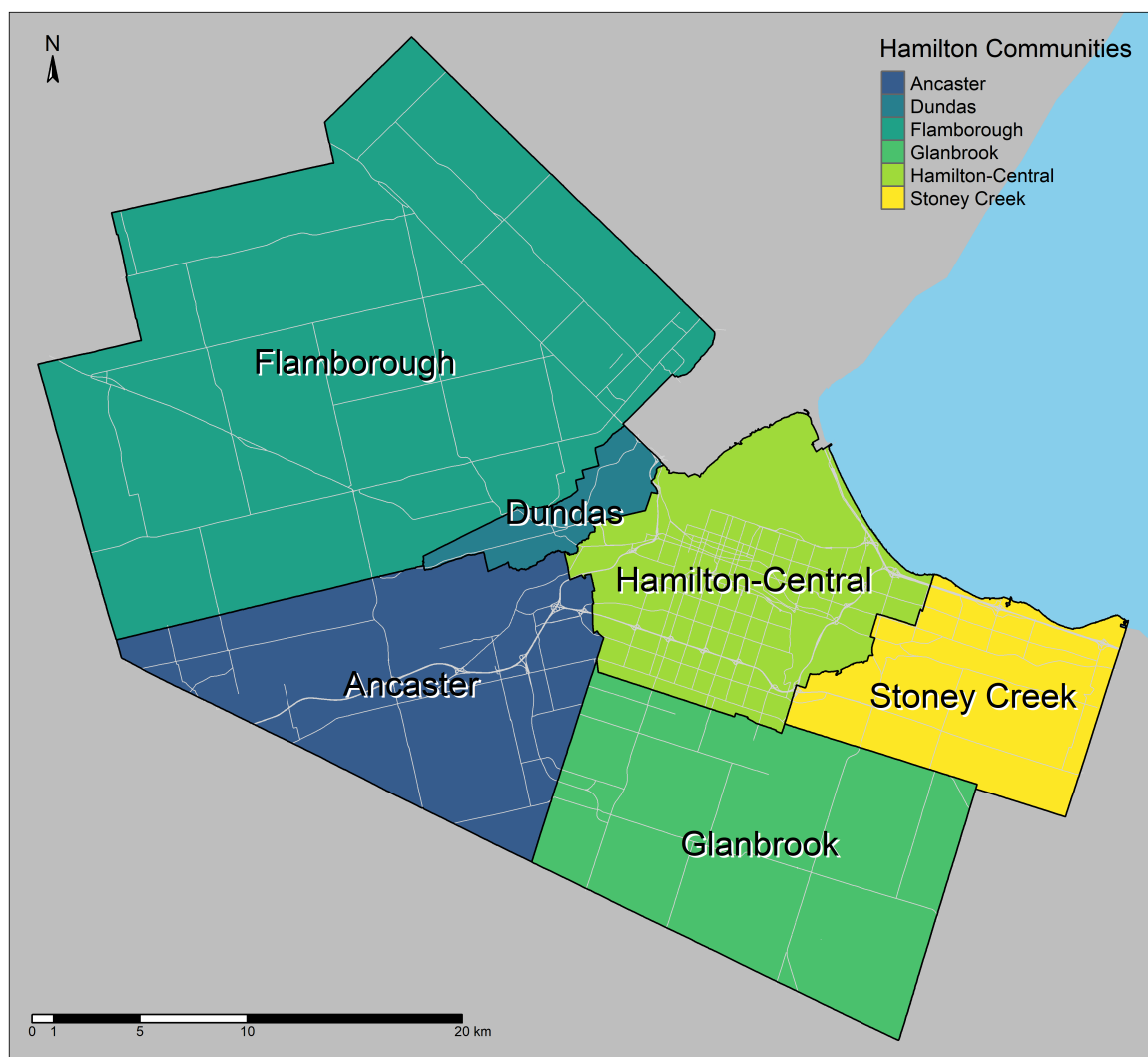


Figure 1: The six former municipal boundaries in the city of Hamilton. Basemap shapefiles are retrieved from the Open Data Hamilton Portal ([Hamilton, 2023a](#)) and the USGS ([USGS, 2010](#)). Highways and arterial roads are shown in light grey.

95 [Hamilton, 2023b](#)), Data Axle, a consumer dataset compiled of businesses and companies within Canada ([Axle](#)  
 96 [Data, 2023](#)) or manually through Google Maps. Each destination was categorized based on the specific type  
 97 of care being accessed following the mobility of care research by Sanchez de Madariaga & Zucchini (2019)  
 98 ([Sánchez de Madariaga and Zucchini, 2019](#)). Categories include child, elder, grocery, health, and errand  
 99 -centric destinations. Category sources of data and preparation notes are detailed in Table 1. Their spatial  
 100 distribution and sub-categories are visualised in Figure 2.

Table 1: Details on the preparation and data sources of care destinations.

Care category	Sources	Data preparation notes
Child-centric	(Hamilton 2022a, 2023, 2022c, 2022d; Ontario 2023b)	<p>Schools, daycares, and community centres, recreation centres, and parks: 1,190 locations are included. After manual review, all locations that typically do not serve children were removed including: Post-Secondary, Adult-Learning Centres, Group Homes, and Foster Care Centres. Further, through examination some Section 23 institutions defined as “<i>centres for children who cannot attend school to meet the needs of care or treatment, and rehabilitation</i>” (Ontario 2023a), were kept due to their innate connection to care.</p>
Elder-centric	(Hamilton 2022d; Ontario GeoHub 2023)	Senior centres, long-term care homes, and retirement homes: 75 destinations are identified.
Grocery-centric	(Axle Data 2023)	<p>Grocery stores, namely a place a household could buy groceries ranging from convenience stores to large retail stores: 381 destinations are identified. Data is filtered by Company Name, Suite Number, Address, City, Province, Phone Number and Postal Code. The type was then identified e.g., grocers specialty foods, grocers retail, grocer health food, grocer wholesale, grocer curbside, grocer delicatessen wholesale, grocer convenience. Data was crossreferenced to ensure all included locations were operational and legitimate grocery stores.</p>

Care category	Sources	Data preparation notes
Health-centric	(Ontario GeoHub 2023; HNHB Healthline 2023)	Hospitals, pharmacies, clinics, and dentist offices: 421 destinations are identified. Hospitals and pharmacies were retrieved while clinics and dentistry clinics were manually scraped from a healthcare services database and checked via Google Maps to remove non-operational locations and confirm dentistry-orientation.
Errand-centric	Hamilton libraries (Hamilton 2022b), post office locations (Axle Data 2023; Canada Post 2023), and datasets of all national bank chains (BMO 2023; HSBC 2023; National Bank 2023; RBC 2023; Scotiabank 2023; TD Bank 2023).	Libraries, post offices, and banks: 158 destinations are identified. Post offices are retrieved from a mix of databases, and duplicates are removed. Banks are also derived from Data Axle and then cross-referenced to ensure data quality with a Bank Locator website for all national banking firms.

For the purpose of this analysis and in absence of city-wide household preferences for care destinations, all locations are re-weighted to make each of the six categories conceptually equivalent i.e., each location within each category  $c$  is weighted to equal  $O_c = \frac{1}{\sum_{c=1}^6 c} \frac{\sum_{c=1}^6 J_c}{J_c}$  where  $J_c$  is the number of locations within a category  $c$ . If this was not done, the results would favour access to child-centric destinations as they make up the majority of the dataset. Accessibility literature has weighted destinations (amenities) using a variety of method such as estimated capacity of destinations (Li and Wang, 2024) or origin-destination flows from travel surveys (Graells-Garrido et al., 2021; Cheng et al., 2019). This work’s focus is on household-serving care destinations, so many destinations do not have traditional ‘capacities’ like health care facilities have beds. Origin-destination flows to all care destinations also have not been counted within the TTS (Data Management Group, 2018a). So, in this analysis, the five care categories are re-weighted to represent one-fifth of the dataset. Conceptually, this simplistic re-weight assumes the population potentially interacts with

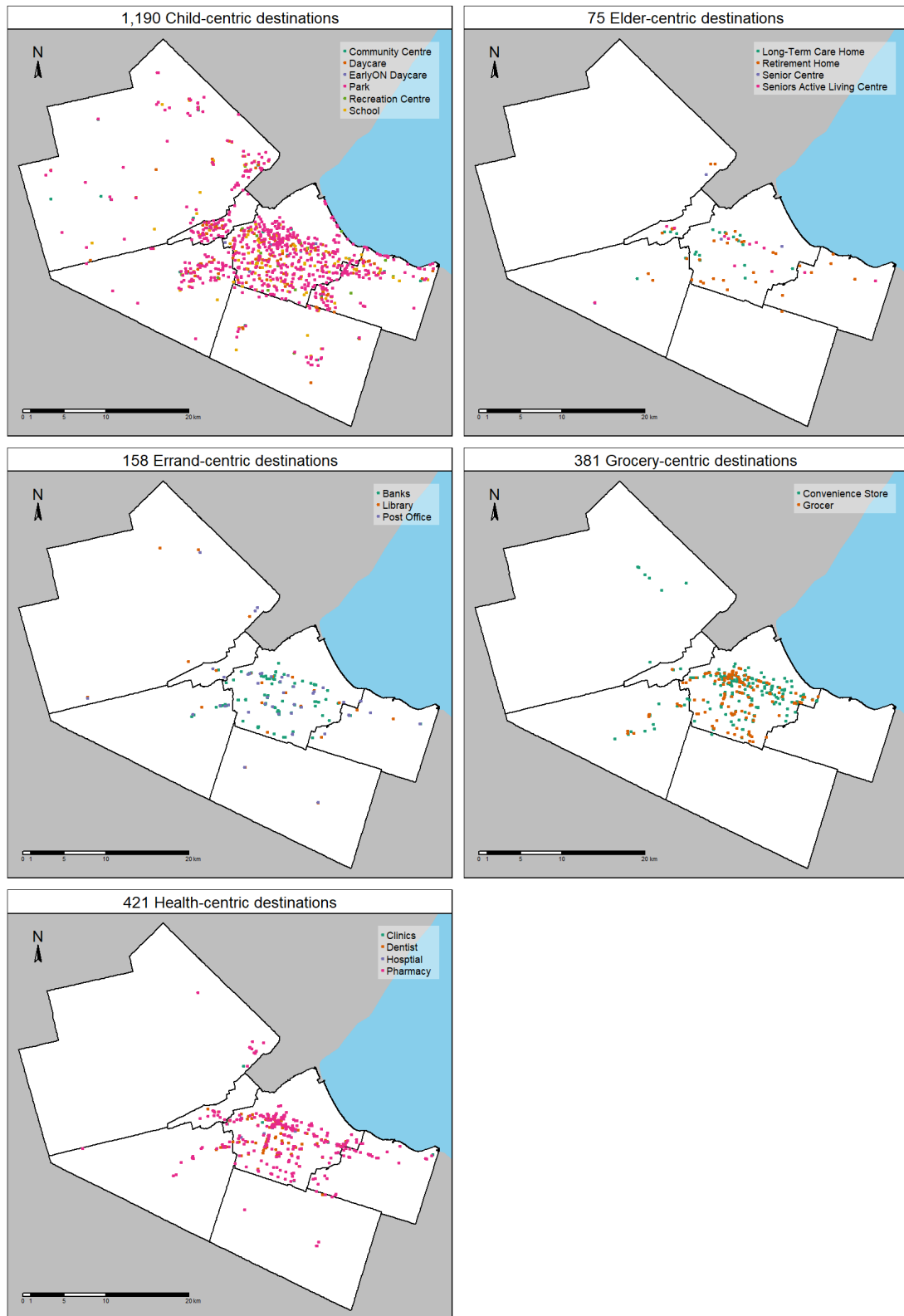


Figure 2: The geo-located points of care destinations in the City of Hamilton separated by the author-generated categories of: child-, elder-, errand-, grocery- and health- centric care categories. Locations of these destinations were retrieved through multiple sources as described in the text. Basemap shapefiles are sourced from the Open Data Hamilton Portal ([Hamilton, 2023a](#)) and the USGS ([USGS, 2010](#)).



all categories and all locations within each category equally. In absence of empirical data for amenity weight calibration, this methodological assumption is a limitation.

- Child-centric (1190 destinations each at 0.3739496),
- Elder-centric (75 destinations each at 5.9333333),
- Errand-centric (158 destinations each at 2.8164557),
- Grocery-centric (381 destinations each at 1.167979) and,
- Health- centric (421 destinations each at 1.0570071) .

## 2.2. Population data

To supplement the care destination dataset and complete the accessibility calculation, population data for the City of Hamilton is sourced from the 2021 Canadian census using the {cancensus} R Package (Statistics Canada, 2023a; von Bergmann et al., 2021). Three categories of variables are selected: the population, the percent of after-tax low-income-cut-off (LICO-AT), and the primary commute mode used. LICO-AT is a composite indicator included in the census that reflects the proportion of households spending 20% more than the area average on food, shelter and clothing (Statistics Canada, 2023b). All data was sourced at the most granular level of spatial resolution publicly available, the level of the dissemination area (DA).

Figure 3 displays the spatial distribution of the total population and the prevalence of LICO-AT as a percentage of the total population. Of note is the density of population within Hamilton-Central (oranges) and the cluster of high density and high LICO-AT prevalence near the shoreline in Hamilton-Central (dark purple-oranges).

Further, the population proportion that commutes by a specific mode (car, transit, walk, or cycle/other) is visualised in Figure 4. Though mode-choice used in travel to work is not necessarily reflective of the mode used to travel to care destinations, to our knowledge no other data is available at a granular level City-wide that centers mobility of care. The population generally commutes by car (50% or higher, is yellow to green), even within the more densely populated Hamilton-Central. However, for transit and walking, a group of DAs near the shoreline within Hamilton-Center have the highest proportion of transit users and those who walk to work (yellows in the plots that are otherwise red i.e., below 15%). Those same DAs are also relatively dense and have a high prevalence of LICO-AT (Figure 3).

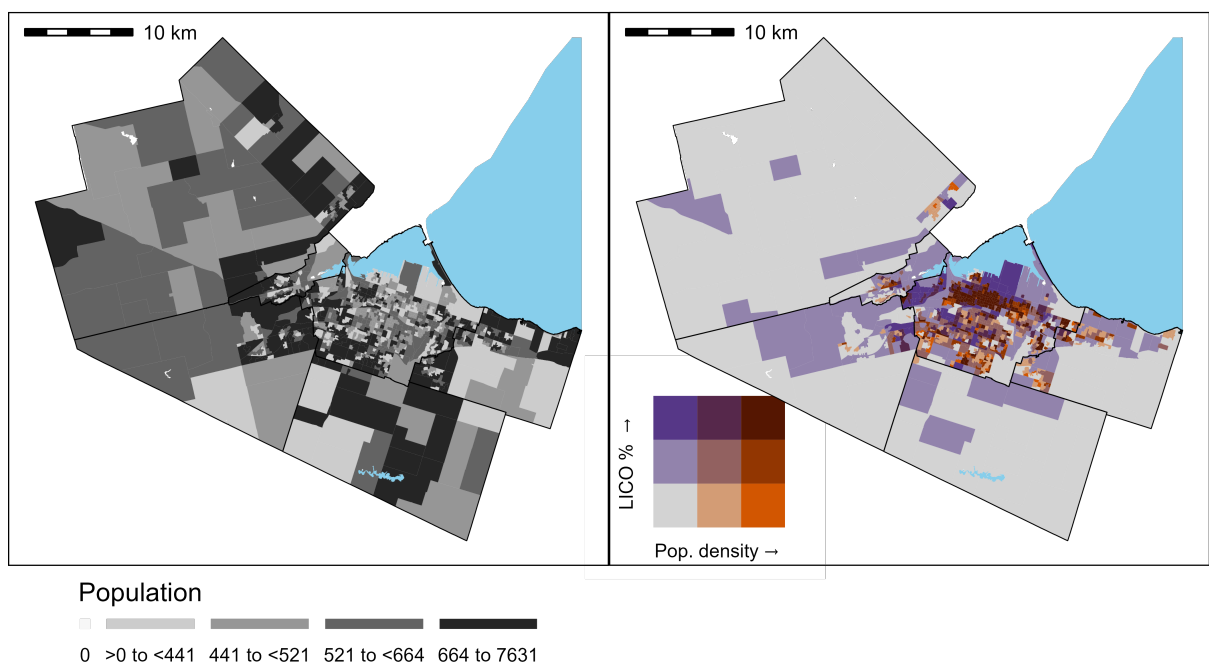


Figure 3: The total population in each dissemination area (DA), visualized with the six former municipal boundaries in the city of Hamilton. The left plot represents the population and the right represents the population density versus the low-income cutt-off after taxes (LICO-AT) as a percentage of the total DA population. LICO-AT is a measure of economic disadvantage. The legend categories represent quartiles. Basemap shapefiles are retrieved from the 2021 Canadian census ([Statistics Canada, 2023a](#)), the Open Data Hamilton Portal ([Hamilton, 2023a](#)) and the USGS ([USGS, 2010](#)).

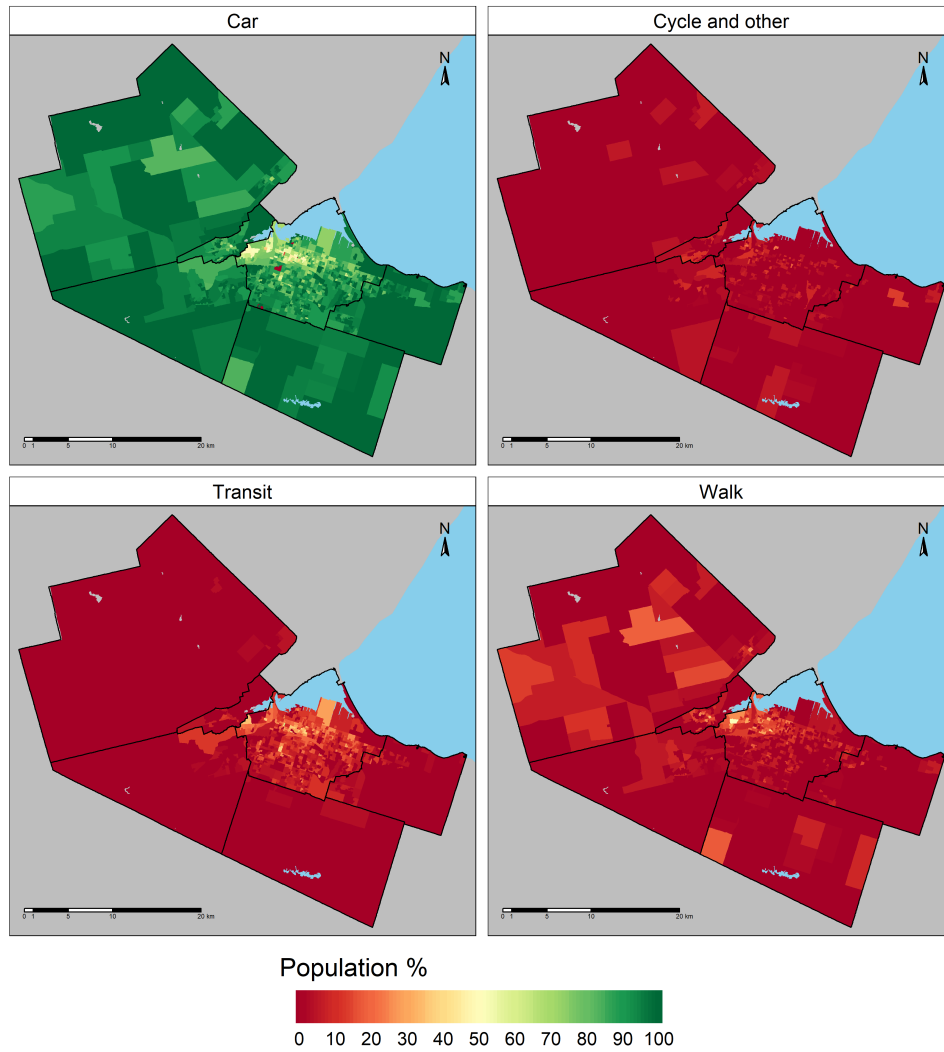


Figure 4: The proportion of mode type used for commuting (aged 15 and older employed in the labour force) in each dissemination area (DA) as provided by the 2021 Canadian census. Basemap shapefiles are retrieved from the 2021 Canadian census ([Statistics Canada, 2023a](#)), the Open Data Hamilton Portal ([Hamilton, 2023a](#)) and the USGS ([USGS, 2010](#)).

### 2.3. Multimodal travel time estimations and accessibility measures

As empirical travel behaviour to care-oriented destinations is uncoun-  
ted, it is approximated in the estimation of travel time to all locations. Travel times by walking, cycling, transit and car is calculated for each DA to the destination point using the ‘travel\_time\_matrix()’ function from the {r5r} package (Pereira et al., 2021). Inputs are point locations of origins, destinations, an OpenStreetMap road network (Geofabrik, 2023), and city GTFS transit routes/schedules (Transit Feeds, 2023). The origin of each DA and destination location is assumed to be its geometric centroid. For all modes, travel times under 60 minutes based on the shortest travel-time path are calculated.

For transit and cycling, additional parameters were included. For transit travel times, a Wednesday departure time of 8:00AM was selected (Boisjoly and El-Geneidy, 2016) with a departure travel window parameter of  $\pm 30$  mins. Travel times are calculated for each minute of the travel window (7:30-8:30AM) and the 25th percentile from the distribution of travel window times were selected to represent each origin-destination. Selecting a sufficiently wide window is an important consideration as travel times are sensitive to transit vehicle frequency and connecting transfers (see discussion of the modifiable temporal unit problem e.g., (Pereira, 2019)). The 25th percentile indicates that 25% of trips from that origin to destination have a travel time that is that length or shorter. This assumption provides an optimistic perspective of transit travel times. For cycling travel times, level 1 or 2 traffic level of stress routes (i.e., dedicated or separated cycling lanes respectively) were selected. The level of traffic stress is a variable associated with links of the OSM road network; level 1 and 2 are considered the default.

The **cumulative opportunity** and **spatial availability** measures are used to estimate the potential access to care that each mode provides to the DA. From the cumulative opportunity measure, the DA level values represent the potential interaction with reachable destinations a population located at DA could access using a given mode. The interpretation of the spatial availability measure is different: each DA level values are a proportional value of all the care destinations in Hamilton. Each proportional value represents the potential availability of reachable care destinations to a mode-using population located at the DA.

**Cumulative opportunity accessibility:** takes the following general form for multi-modal calculation:

$$S_i^m = \sum_j O_j \cdot f^m(c_{ij}^m)$$

Where:

- $i$  is a set of origin locations.
- $j$  is a set of destination locations.
- $m$  is a set of modes.
- $O_j$  is a number of opportunities at  $j$ , in our case weighted.
- $c_{ij}^m$  is the travel cost between  $i$  and  $j$  for each  $m$ .
- $f^m(\cdot)$  is an impedance function of  $c_{ij}^m$  for each  $m$ ; within the cumulative opportunity approach, it is a binary function that takes the value of 1 if  $c_{ij}^m$  is less than a selected value (Handy and Niemeier, 1997).
- $S_i^m$  is the unconstrained accessibility for  $m$  at each  $i$ .

**Spatial availability**, on the other hand, takes the following general form for multi-modal calculation:

$$V_i^m = \sum_j O_j F_{ij}^{tm}$$

Where:

- $i, j$ , and  $m$  is a set of origin locations, destination locations, and modes respectively.
- $O_j$  is a number of opportunities at  $j$ , in our case weighted.
- $F_{ij}^{tm}$  is a balancing factor for each  $m$  at each  $i$ . It depends on the size of the populations at different locations that demand opportunities  $O_j$ , as well as the cost of movement in the system  $f(c_{ij})$ .
- $V_i^m$  is the constrained accessibility (spatial availability) for  $m$  at each  $i$ ; the sum of  $V_i^m$  for all  $m$  at each  $i$  is equivalent to the total sum of opportunities in the region (i.e.,  $\sum_j O_j = \sum_i V_i = \sum_m \sum_i V_i^m$ ).

What makes spatial availability stand apart from other competitive measures is the multimodal balancing factor  $F_{ij}^{tm}$  (see Soukhov et al., 2024, 2023).  $F_{ij}^{tm}$  implements a proportional allocation mechanism that ensures the sum of all spatial availability values at each  $i$  always matches the total number of opportunities in the region.  $F_{ij}^{tm}$  consists of two parts: the first is a population-based proportional allocation factor  $F_i^{pm}$  that models the mass effect (relative population-demand for opportunities) and the second is an impedance-based proportional allocation factor  $F_{ij}^{cm}$  that models the cost effect (relative travel time). Both factors consider competition through proportional allocation:  $F_i^{pm}$  estimates a proportion of how many people are in each  $i$  and using each  $m$  relative to the region and  $F_{ij}^{cm}$  estimates a proportion of the cost of travel from

191  $i$  to  $j$  at each  $i$  using each  $m$  relative to the region. Since  $F_i^{pm}$  and  $F_i^{mc}$  are proportions,  $\sum_m \sum_i F_i^{pm} = 1$   
 192 and  $\sum_m \sum_i F_i^{cm} = 1$ . Both factors are combined to create the total balancing factor  $F_{ij}^{tm}$  used to calculate  
 193  $V_i^m$ :

$$F_{ij}^{tm} = \frac{F_i^{pm} \cdot F_{ij}^{cm}}{\sum_m \sum_i F_i^{pm} \cdot F_{ij}^{cm}}$$

194 Where:

- 195 • The factor for allocation by population for each  $m$  at each  $i$  is  $F_i^{pm} = \frac{P_i^m}{\sum_m \sum_i P_i^m}$ . This factor makes  
 196 opportunities available based on demand.
- 197 • The factor for allocation by cost of travel for each  $m$  at  $i$  is  $F_{ij}^{cm} = \frac{f^m(c_{ij}^m)}{\sum_m \sum_i f^m(c_{ij}^m)}$ . This factor makes  
 198 opportunities available preferentially to those who can reach them at a lower cost.

199 The travel impedance threshold used in both measures is 15 minutes and 30 minutes; each measure is  
 200 calculated eight times, once for each four modes and assuming a travel time cut-off of 15 minutes or less  
 201 and another assuming a travel time cut-off of 30 minutes or less. The selection of travel time thresholds is  
 202 informed by the literature. Only one study to date has calculated the average travel time to all different  
 203 categories of care destinations (16 minutes by car and 36 by public transport) ([Ravensbergen et al., 2022](#)).  
 204 Other literature typically considers trips to one type of care category (e.g., health, or school, or grocery stores)  
 205 Here, travel times vary by care category (e.g., 15 minutes to grocery shopping ([Hamrick and Hopkins, 2012](#))  
 206 or 20.45 for cancer treatments ([Segel and Lengerich, 2020](#)). In other care-related accessibility analyses, time-  
 207 cut offs include 10 mins (for daycares) ([Fransen et al., 2015](#)) and 30 mins to 1 hr (for hospitals) ([Schuurman](#)  
 208 [et al., 2006](#)). 15 and 30 minutes were selected to broadly reflect this past research. The use of a binary travel  
 209 time threshold, as opposed to more complex impedance functions, was selected to simplify communication  
 210 of assumed travel behaviour. As mentioned, lacking region-specific empirical data regarding care-centric  
 211 travel, this work establishes a methodology to streamline access to care interpretation and analysis for when  
 212 that data is available.

213 This work uses both constrained and unconstrained accessibility measures to elucidate different interpre-  
 214 tations of access to care. As an unconstrained measure, cumulative opportunity measure counts all the  
 215 destinations that can be reached from each DA within a travel cost, for each DA. From a region-wide per-  
 216 spective, a destination that can be reached is counted multiple times by all DAs that can reach it, so the sum  
 217 of all cumulative opportunity DA values in the region is not meaningful. Simply, if walking-mode provides

access to some number of opportunities within a 30 minutes, car-mode provides some greater access within 30 minutes, and the access that walk-mode is not discounted by the population using car-mode and the greater number of opportunities they can potentially access. However, cumulative opportunity measure is intuitive to implement, a part in why it has been widely adopted in accessibility research and considered a introductory method to more advanced accessibility measure (El-Geneidy and Levinson, 2021).

On the other hand, spatial availability is constrained accessibility measure that considers competition (Soukhov et al., 2023). It incorporates the concept of the *finite*: opportunities are numbered in the region so they can be potentially interacted with more or less based on the travel impedance offered by the zone (i.e., the travel cost on the transport network) as well as how densely or sparsely the zone is populated with opportunity-seeking opportunities. This is especially important considering population-distinct characteristics like selected travel modes. In a North American context, car-modes can potentially access more opportunities (unconstrained) because of their higher range relative to transit. But if opportunities are considered finite, high car mobility may take-up a higher share of opportunities from populations using modes that offer lower mobility, especially in zones where there is a high population and car-using modal split. Cumulative opportunities does not consider the relative population-demand for care destinations while spatial availability does: the use of these two measure illustrates distinct results.

### 3. Results

#### 3.1. Unconstrained access to care

The cumulative opportunity accessibility plots for each mode are shown in Figure 5. They visualise an unconstrained count of care destinations that can be reached by each mode from each DA. The higher the zonal value, the more potential interaction with care destinations. This greater potential is conceptualised as a positive outcomes of well functioning land-use and transport networks (Cordera et al., 2019; Blumenberg and Pierce, 2017; Cui et al., 2020). Spatial trends between the 15-min and 30-min threshold plots are similar (values are grouped by quantile). Three significant findings between modes can be identified. First, the access that the car-mode provides is significantly higher relative to other modes. Travel by car results in the greatest maximum number of potential interactions to care destinations (1939 opportunities for 15-min and 2209 opportunities for 30-mins). Next, access by cycling is also relatively high. It provides the second most opportunities for interactions after travel by car, and affords at least one opportunity for interaction in more DAs than walking and transit use. Finally, access by transit is high and walking is also relatively high within Hamilton-Central but low elsewhere.

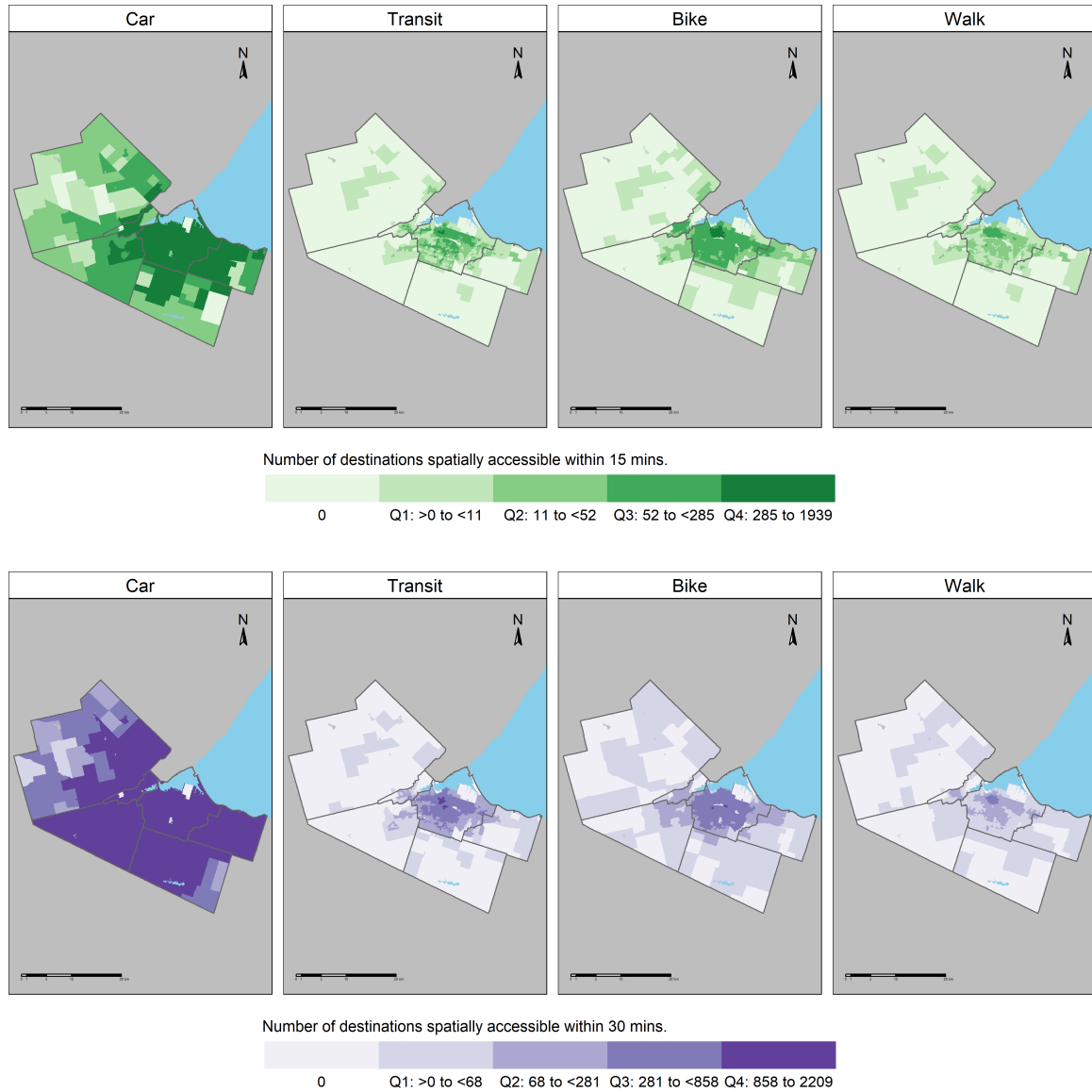


Figure 5: The cumulative opportunity measure. The number of care destinations that can be reached, per DA, within 15 mins (top) and 30 mins (bottom). Basemap shapefiles are retrieved from the 2021 Canadian census ([Statistics Canada, 2023a](#)), the Open Data Hamilton Portal ([Hamilton, 2023a](#)) and the USGS ([USGS, 2010](#)).



From Figure 5, car-mode offering high accessibility to destinations is an expected outcome given the car-oriented design of North American cities (Saeidizand et al., 2022). However, access by non-car modes is great within many DAs in Hamilton-Central (Q3 and Q4). As well, cycling provides some access to destinations (Q1) in more rural communities. While car ownership is high in Hamilton, not everyone has access to a private vehicle: 13% of Hamilton households own zero vehicles (Data Management Group, 2018b). Unconstrained access is insightful in illustrating the spatial accessibility to destinations that people may have, but it does not account for how the overall access provided by the transportation systems to destinations is allocated to different mode-using populations. This lack of consideration may conjure misleading conclusions, namely the inflated promise of lower access-providing modes.

### 3.2. Constrained access to care

Consider cycling: the access provided by this mode appears promising when examining the cumulative opportunity results (Figure 5). This may be in part because interpreting cycling access against the much higher access providing car-mode is difficult. Unconstrained access by car is high (Q4), but at least cycling-mode can achieve Q3 levels in Hamilton-Central and Q1 beyond. However, by conceptualising the amount of accessibility available in the region as a total, one can answer how many opportunities are available to those using the cycling-mode considering the allocation to the other three mode-using populations. This comparison cannot be addressed using unconstrained accessibility, but can be explored with spatial availability (constrained accessibility), mapped in Figure 6.

This study's calculation of spatial availability (Figure 6) assumes population mode-shares (proportions shown in Figure 4), while the unconstrained analysis does not. In this context, from Figure 6 it can be observed that those who use car-modes are allocated the most spatial availability i.e., the proportion of spatial access to destinations out of all spatial access to destinations in the region. A similar spatial trend is found in the unconstrained accessibility analysis (Figure 5). However, since Figure 6 accounts for the mode-using population, the results are more rich. Spatial availability for motorists is in-part due to the exceptionally high proportion of car-using populations (especially in rural communities) as well as car-mode's relatively competitive travel time. There is a higher car-using population and the car-mode has low travel times to destinations allowing the car-mode using population in each DA to capture the majority of spatial availability. Figure 5 only sheds light on how much unconstrained accessibility the car-mode could potentially provided to people within a DA.

While the unconstrained accessibility analysis (Figure 5) demonstrates that non-car modes are promising

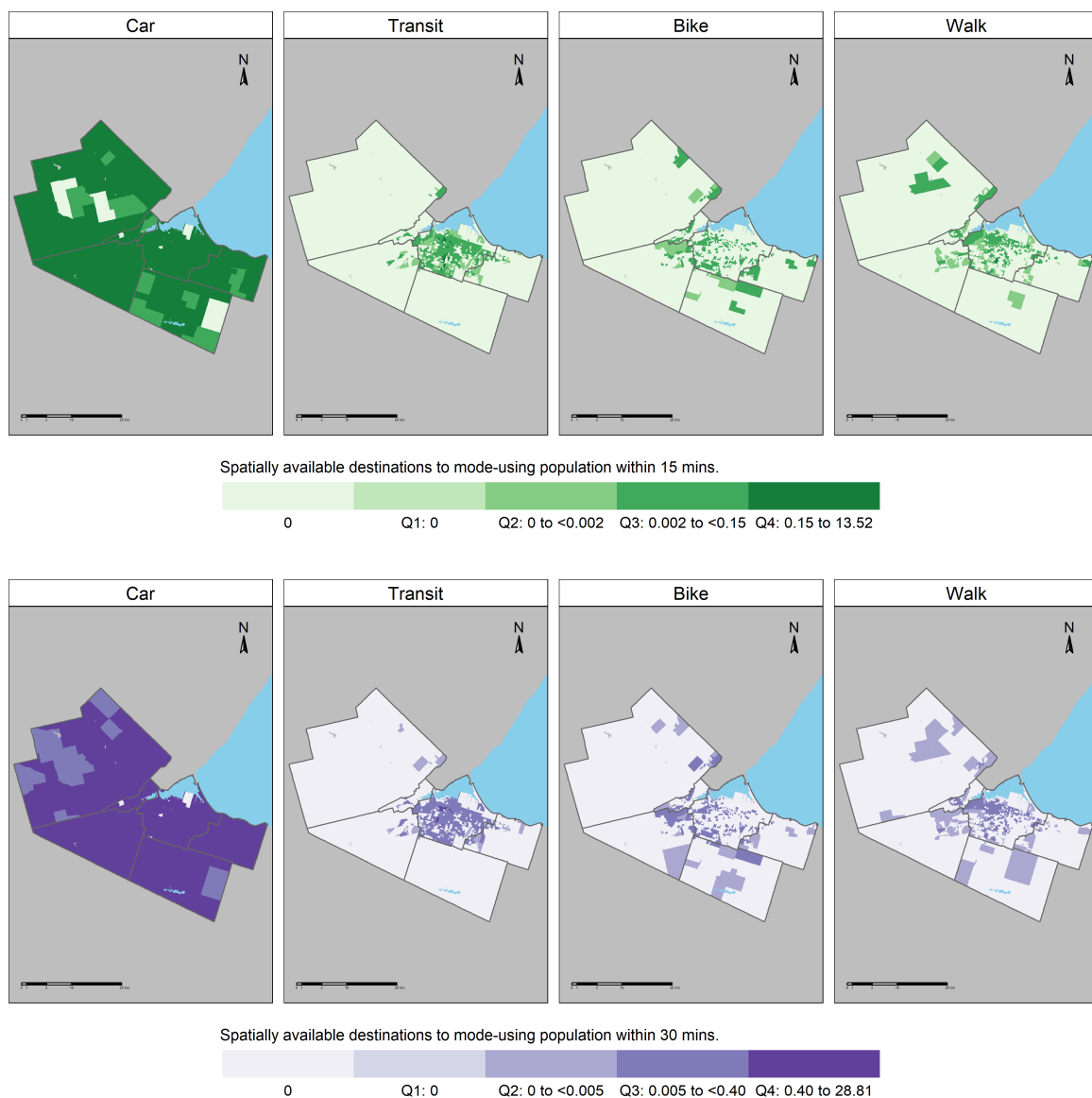


Figure 6: Spatial availability: the number of care destinations that can be reached, per DA, within 15 mins (top) and 30 mins (bottom). Basemap shapefiles are retrieved from the 2021 Canadian census ([Statistics Canada, 2023a](#)), the Open Data Hamilton Portal ([Hamilton, 2023a](#)) and the USGS ([USGS, 2010](#)).

in urban areas, as well as cycling in rural communities, Figure 6 demonstrates a more nuanced perspective. Though non-car modes may provide good unconstrained accessibility within Hamilton-Central (and some access in rural communities), they do not provide similar levels of spatial availability. Car-using populations capture more spatial availability, even in the centre of Hamilton-Central, than all other modes. Note the lower number of Q3 and Q4 values within and radiating outwards from Hamilton-Central for non-car modes in Figure 6 compared to Figure 5. Differences between the two measures follow a similar descriptive trend for both travel times.

The proportion of spatial availability allocated to a mode-using population can also be directly compared. This sheds light on what mode, and in what region, a mode-using population captures more than its equal share of spatial availability. Overall, 97% of the spatial availability is taken by motorists (destinations within 30-minutes) but they only represent 87% of the population; they have disproportionately more availability than their population’s presence in the city. They capture this availability from non-car mode using populations that exists in high proportions with lower spatial availability (i.e., transit users to destinations within 30-minutes are 7% of the population but take 2% of the spatial availability, 30-minute cyclist are 2% of the population but represent 0.3% of the spatial availability, and 30-minute walkers are 4% of the population but are allocated 0.3% of the spatial availability).

The key interpretation from Figure 6 is that if certain modes capture an exceptional proportion of availability, then the availability left for other modes is lower overall. This does not necessarily have to align with the unconstrained accessibility that mode offers. As noted, non-car modes have the potential to offer higher unconstrained access (within Hamilton-Central) in Figure 5. But as it exists (assuming modal commute shares), the majority of spatial availability to care destinations can still be captured by motorists even in DAs where car mode share is under 50% (such as Hamilton-Central, see proportions in Figure 4).

### 3.3. Equity considerations

To draw insights on who may reside in DAs where populations are advantaged with higher modal spatial availability, a cross-tabulation of low-high spatial availability & LICO-AT prevalence and high-no spatial availability & LICO-AT prevalence is visualised in Figure 7. The modal spatial availability is divided by the mode-using population in each DA, resulting in the rate of modal spatial availability. LICO prevalence is the proportion of population that falls below the LICO-AT (see Figure 3). Figure 7 can be interpreted as follows: residents who use a specific mode in a “yellow” DA reside in a DA that offers below average spatial availability (i.e., below or equal to the the 50th percentile (median) levels of spatial availability per

mode-using population) and the population within the DA has a high LICO-prevalence (i.e, 80th percentile or higher (8.4% or more)).

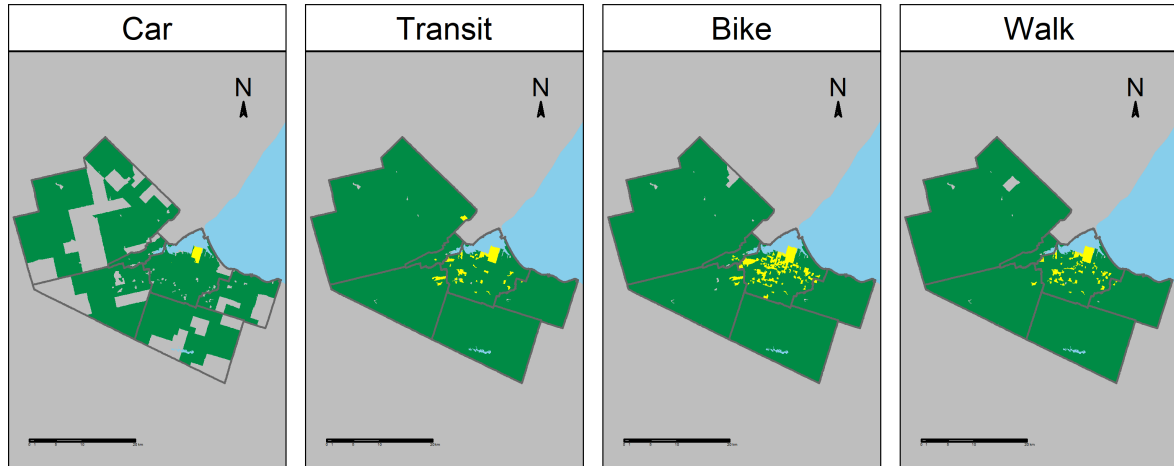
Notice the green DAs for the car-driving population and presence of yellow DAs for non-car modes within Hamilton-Central: Figure 7 reinforces findings from Figure 6. Even in Hamilton-Central where there is high proportion of LICO-AT prevalence, car-mode using populations who reside in green DAs are still offered high levels of spatial availability. However, car ownership is not always possible for low-income households and the lack of ownership acts as a barrier to accessing economic and economic-support opportunities for low-income households (Morris et al., 2020) when alternative modes are insufficient (Klein et al., 2023). For this reason, populations below the LICO-AT may rely on non-car modes, and the introduction of policies that increase access to care-destinations could be considered. The majority of yellow DAs are within the centre of Hamilton-Central, specifically for cycle- and walking populations. Policies that increase the number of available care-destinations within Hamilton-Central, improve conditions that decrease LICO-AT prevalence, as well as policies that make car-modes less spatial availability advantaged (i.e., encourage modal shift and decrease travel time) could be further investigated through the lens of mobility of care.

#### 4. Discussion and conclusions

This paper is the first to conduct an exploratory feminist accessibility analysis of care destinations – one that counters the current literature’s emphasis on employment-related travel, a travel more significant for men, and especially wealthy and educated men (Law, 1999; Hanson, 2010). Its aim is to challenge current planning paradigms by explicitly focusing on care, vital and life-sustaining activities that are undervalued, and to provide a tangible example of how one could gender-mainstream accessibility analyses. In doing so, it contributes to the emergent mobility of care literature, a body of what that has, to date, focused on quantifying this under-represented type of travel (Gómez-Varo et al., 2023; Murillo-Munar et al., 2023; Ravensbergen et al., 2022; Sánchez de Madariaga, 2013; Sánchez de Madariaga and Zucchini, 2019; Shuman et al., 2023) and has provided rich and nuanced qualitative accounts of lived experiences completing mobility of care (Orjuela and Schwanen, 2023; Ravensbergen et al., 2020; Sersli et al., 2020).

This paper also contributes to accessibility research by implementing both an unconstrained (cumulative opportunities) and constrained (spatial availability) multimodal accessibility measure. The unconstrained measure demonstrates the potential interaction with care destinations that each mode offers from each DA within a 15- and 30- minute travel time thresholds. The constrained measure incorporates the assumed

### Within 15 minute travel time



### Within 30 minute travel time

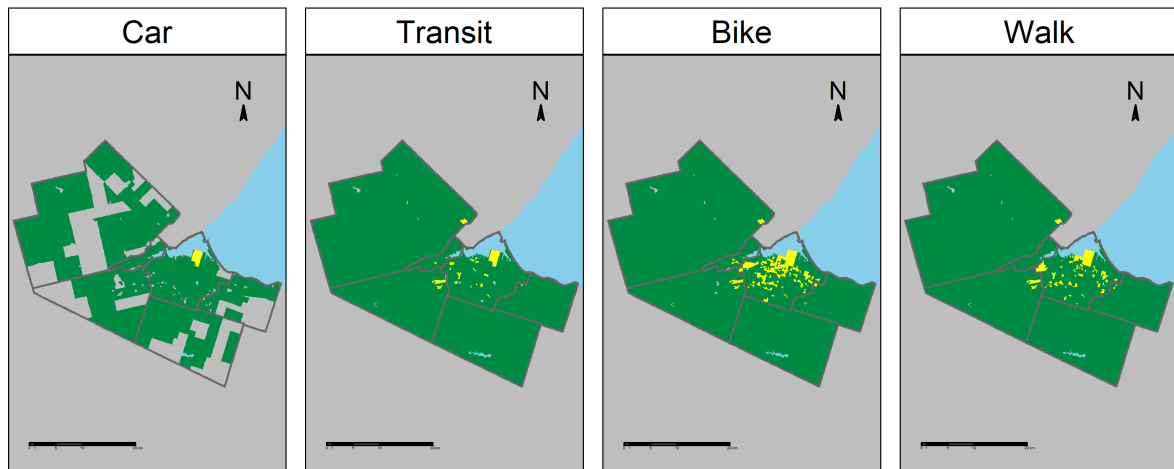


Figure 7: The spatial availability per mode-using-capita measure versus high-income cut-off . The number of care destinations that can be reached per mode-using-capita, per DA, within 15 mins (top) and 30 mins (bottom). Basemap shapefiles are retrieved from the 2021 Canadian census ([Statistics Canada, 2023a](#)), the Open Data Hamilton Portal ([Hamilton, 2023a](#)) and the USGS ([USGS, 2010](#)).

proportion of mode-using population and mode-specific travel time to demonstrate the potential interaction with destinations that each DA has available to a mode-using population. The distinction between the constrained and unconstrained measures are clarified, namely that potential interaction may be over-inflated, especially for the lower range non-car modes, when considering unconstrained access over spatial availability. Unconstrained access may demonstrate over-inflated promise for active transport modes. The consideration of both unconstrained and constrained access can encourage a shift in perspective. Motorists are generally estimated high unconstrained access to many care destinations as well as exceptionally high spatial availability. Those who use alternative modes, have low unconstrained access and, in certain DAs, and even lower level of availability. This is as a result of car-using populations being allocated a disproportionate number of total care destinations. Spatial Availability is a way of conceptualising accessibility as a city-wide total and each calculated value is a proportion so it can be easily placed relative to all others in the city. However, it relies on assumptions on who is “demanding” the destinations, and how those assumptions are made are a subject of ongoing discussion in how accessibility considers competition (Merlin and Hu, 2017; Kelobonye et al., 2020).

Further, this study contributes to the literature on sustainable travel behaviour. Results indicate that care is most easily accessed in Hamilton by car, an unsurprising result given its car-oriented design. Previous research has found that mobility of care are more frequently completed by car or by foot than by transit or by bicycle (Ravensbergen et al., 2022). It is possible that the car’s ability to provide higher access to care destinations, as observed in this study, shapes this tendency to complete care trips by car. Car use may also be more frequent for care trips because these trips tend to involve carrying things (e.g., groceries) or people (e.g., children). Indeed, past qualitative work has found that many prefer travelling by car for this type of trip due to convenience and increased safety (Maciejewska and Miralles-Guasch, 2019; Carver et al., 2013). Then again, care trips tend to be shorter than other trips (Ravensbergen et al., 2022), making them ideal for more sustainable travel modes, such as active modes (walking, cycling) and public transport. The low access to care by foot identified in this study is discouraging, given both people’s tendency to use this mode for care trips (Ravensbergen et al., 2022), and the benefits of walking as a travel mode, both for individuals, cities, and the environment. Somewhat unexpectedly, access to care was found to be low by transit and by foot and relatively high by bicycle. Given that low income women, in particular, seem to be transit reliant for care trips (Ravensbergen et al., 2022), this result highlights both a potential bias against care trips by transit and the equity implications of that bias. Though past work has found that many barriers exist for cycling for care (Ravensbergen et al., 2020, 2019; Sersli et al., 2020), the results of this study highlight the

great potential of the bicycle for easily accessing care.

The preliminary nature of this research also comes with its limitations as a result of data availability. The accessibility results are not calibrated to reflect observed mobility-to-care travel behaviour due to data unavailability nor are they formulated to express any normative accessibility goals. Instead, they present a preliminary exploration of how the mobility of care concept could be operationalised within accessibility analysis.

First, the travel time estimations assume free-flow network conditions: while impacting estimated travel times, estimated congested conditions may not have a drastic impact on spatial accessibility calculations (Yiannakoulis et al., 2013), especially for cycling and walking modes. Second, the use of a binary travel time cut-off instead of a more complex travel impedance function can have a significant impact on accessibility results. To add reliability, two literature-informed travel cost thresholds (15-minutes and 30-minutes) were selected, but results' interpretation are hampered by the binary function selection: some zonal populations could *still* value destinations beyond a 30-minute travel time, and some populations may not see a destination 5 minutes and 15 minutes away as necessarily equal in travel impedance. Third, the geometric centroids of DAs (origins) and destinations (all care destinations) were used as inputs for travel time calculations. DAs are created for the purpose of the census: they vary in area and centroids may not necessarily align with where that population may begin their journey to care destinations. Fourth, the quality, importance and specific willingness to travel to types of care destinations for mode-using populations within a zone was not considered as data is unavailable city-wide. As such, this study assumes each destination is 1 opportunity and re-weights each of the five care categories to be conceptually equal. Fifth, the mode choice for care destinations trips is unknown and hampers interpretation of spatial availability. It is assumed in the study to be equal to the work-commute mode selection, but this is may not be necessarily the case.

Future work could look to address these limitations as well as compare access to care results to conventional access to work landscapes. This comparison could highlight the bias in planning towards jobs as well as substantiate equity critiques.

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## 5. Appendix

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