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Which access matters? A comparative analysis of accessibility metrics and their impacts on commuting

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Abstract: Accessibility, a transport and land-use performance metric, is an umbrella term for several methodological approaches quantifying access to opportunities that can impact travel behavior. Some accessibility measures are easy to estimate and interpret, although they are based on restrictive assumptions, while others are more realistic but impose higher requirements for inputs, estimation, and interpretation. Selecting the measure of accessibility to incorporate in planning practice is a continuous challenge that professionals face. In this paper, we compare the strength of association between non-competitive and competition-based opportunity measures and the share of transit mode users at the Census Tract level of analysis in Toronto, Montreal, and Vancouver, Canada. Our findings confirm the positive association between all accessibility measures to jobs by public transit and transit mode share and identify that the simple cumulative opportunities calculated at the mean transit travel time of the region and gravity-based measures result in higher explanatory power compared to more complex competition-based measures, with a negligible level of difference between the former two. The insights from this paper can be of value to analysts and practitioners seeking to select accessibility measures that are representative of real conditions, easy to calculate and interpret, and with high predictive power of travel behavior in planning practice.

Keywords: Cumulative accessibility, gravity-based accessibility, competition-based accessibility, spatial availability, transportation equity, public transit

1 Introduction

Investments in public transit (PT) have moved to the forefront of transport policies to reduce the amount of transport-related pollution through getting more people out of personal vehicles to use public transit (Beaudoin et al., 2015; Hoppe et al., 2023). One of the measures that can help guide transport planning decisions in that direction is accessibility, as it effectively represents the ease of reaching destinations using a specific mode. Accessibility is an umbrella term for several methodological approaches quantifying access to opportunities that impacts travel behavior (Cui et al., 2020; Legrain et al., 2015). However, selecting the appropriate measure of accessibility to incorporate in planning practice is a continuous challenge for professionals who have to tradeoff between cost and ease of communication of measures to the decision-makers and the general public (Boisjoly & El-Geneidy, 2017; Siddiq & Taylor, 2021). As a result, despite strong support from academia (El-Geneidy & Levinson, 2022; Handy, 2020; Miller, 2018), accessibility has experienced only limited application in practice. While the recent years have seen some slight progress in the adoption of accessibility measures in planning practice, in part facilitated by the introduction of open-source tools like the r5r package (Pereira et al., 2021) exemplified in Atlanta, Portland, Dallas, and the State

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of Washington, and other major metropolitan regions in the US, Toronto, British Columbia, and national proximity measures database in Canada, Paris and London in Europe, or Sydney in Australia (Center for Transportation Studies, 2025; Deboosere & El-Geneidy, 2018; Higgins et al., 2022; Statistics Canada, 2020; WSDOT, 2023), the scale of adoption is still far from an established practice among the practitioners. Currently, cumulative, gravity-, and competition-based measures are the most commonly used accessibility measures in transportation planning and research (Demitiry et al., 2022).

The concept of accessibility was first introduced in the mid-twentieth century by Hansen (1959) as the potential for opportunities for interaction. He used a gravity-based measure to better understand and predict development. Over the years, others introduced measures such as the cumulative opportunities measure, which is simpler and straightforward to calculate (Wachs & Kumagai, 1973). Later on, more complex and data-intensive measures such as the utility-based measures, were introduced (Ben-Akiva & Lerman, 1979). Meanwhile, the advancement in computational power allowed for the introduction of more realistic, yet harder to interpret and compute competition-based access measures (Paez et al., 2019; R. Pereira et al., 2021; Shen, 1998). Yet, there has been only limited work focusing on a comparison of the predictive power of these different measures of mode choice for transport planning purposes.

Accessibility is one of the factors that has been observed to influence transportation mode choice (Levinson & Kumar, 1994), together with sociodemographic characteristics of the traveler, built environment, traffic conditions, and quality of the transit service (Eluru et al., 2012). Across these components, accessibility stands out as an actionable and comprehensive measure that can both inform and guide transport planning towards more sustainable societal outcomes (El-Geneidy & Levinson, 2022; Handy, 2020), like the use of transit. Conceptually, this can be explained from the perspective of random utility theory (RUT) (Ben-Akiva & Lerman, 1979), with transit use going up when accessibility increases because it raises the expected utility of transit relative to alternatives. On the other hand, from the point of view of time geography (Hägerstrand, 1970), more accessibility expands the feasible activity space by making more opportunities, like jobs, reachable by transit, increasing the feasibility of transit-based activity patterns. These, in turn, can positively impact attitudes towards transit, perceived behavioral control (due to an increase in access), and subjective norms when it comes to transportation mode choice, all leading to potential behavioral change as stipulated in the theory of planned behavior (Ajzen, 1991). Overall, there are both theoretical and methodological foundations to believe that accessibility can improve societal outcomes if more guidance is provided on its application and the choice of appropriate measures in planning and practice.

This study aims to compare non-competitive (cumulative, gravity-based) and competition-based accessibility measures in their ability to explain public transit commuting mode share in three largest Canadian metropolitan regions - Toronto, Montreal, Vancouver, and to determine if a simpler and easier to compute approach (i.e., cumulative) can be as effective in predicting PT mode share compared to more resource-intensive and realistic proxies (competition-based measures). At their core, competition-based measures are well-suited to capture the outcomes of access to scarce opportunities, such as health, because of timely medical assistance due to the availability of hospital beds or doctors, or employment, because of job openings not fulfilled due to existing competition. Yet this increase in accuracy comes at a cost of additional requirements for data and skills compared to simpler methods. Moreover, in the context of regional transport planning, and particularly when applied to guide and promote changes in travel behavior towards more sustainable travel modes, like transit, the evidence for the need for this additional complexity is lacking.

Overall, this paper tests the hypothesis that more complex competition-based accessibility measures do not offer significant improvements to the insights into the effects of accessibility on travel choices in a general context, like employment. The findings equip practitioners and researchers with evidence to justify cost savings in data collection and analysis when conducting accessibility assessments. In doing so, our paper follows the spirit of the Kapatsila et al. (2023) study that found cumulative accessibility to employment calculated for the average travel time in the region to provide an equally representative measure of opportunity, like more complex gravity-based approaches. As such, the goal of our study is to promote a broader adoption of accessibility in transport planning practice by offering evidence that simpler methods, like the cumulative accessibility measure, are a reliable proxy for operationalization and to guide analysts and decision-makers in their selection process of a suitable and cost-efficient accessibility tool to use in transport planning.

2 Literature review

The emergence of accessibility as a concept has been historically motivated by the desire to develop the means of assessing the impact of planning projects on land use and transport systems (Morris et al., 1979). This literature review covers the evolution of various approaches to measuring accessibility, studies that compared the reliability of different measures, and the reported effect of accessibility measures on travel behavior. At the same time, we do not include the literature on changes in accessibility from investments in transport infrastructure, network redesign, and its applications for local self-sufficiency planning of various parts of the cities (i.e., 15-minute cities), since those are outside of the scope of our paper.

2.1 Methodological approaches to accessibility

Hansen (1959) offered a straightforward approach to quantify the effect that the number of jobs, people, and services had on land-use development in Washington, D.C. In the calculations, he used an exponential decay function for travel time to capture the penalty of longer trips, making places that are farther out less attractive to a traveler, which was later named the gravity measure of accessibility (Koenig, 1980). Gravity-based measure received broad support in the academic community (Geurs & van Wee, 2004; Siddiq & Taylor, 2021) as it corresponds to the decline in consumer surplus due to the longer travel times (Cochrane, 1975). This method, however, may impose additional requirements for data inputs, depending on the form of the impedance function, and provides results that are less intuitive for communication (Handy & Niemeier, 1997). To overcome this data and interpretation complexity, some researchers suggested simply quantifying the number of opportunities, like jobs, that can be reached within a certain amount of time, like 30 or 45 minutes (Wachs & Kumagai, 1973). Commonly labeled as cumulative access, it provides an aggregate measure of accessible opportunities that someone traveling on a certain mode can reach within a defined travel time (Ingram, 1971). On the other hand, if the travel time is longer than the selected threshold, the opportunities are deemed not accessible. It is fairly easy to quantify and communicate, this simplicity is oftentimes the reason for criticism, since the motivation for the selection of the cutoff time varies across different studies (Páez et al., 2012). While there is no doubt in the additional benefit of using gravity-based measures for accurate assessment of accessibility, Kapatsila et al. (2023) has shown that from the perspective of the regional planning, the outcomes of cumulative accessibility calculated for the mean travel time in the region are comparable to the estimates of gravity-based measures in eight Canadian metropolitan areas of various size. It also corroborated the findings of an earlier study by El-Geneidy and Levinson (2006) that was more limited in scope. On the other hand, when looking at the changes in accessibility from transit project improvements in two Canadian regions, Klar et al. (2023) found cumulative and gravity-based measures to be only moderately correlated, though their assessment used a 90-minute threshold for time budget, instead of the actual mean travel time in the region.

In the meantime, cumulative opportunities and gravity-based measures received some criticism in the literature as they ignore competition, bringing in the notion that opportunities should become unavailable once consumed by some of the population (Kelobonye et al., 2020; Merlin & Hu, 2017; Paez et al., 2019), like hospital beds or emergency shelter spaces. This idea is at the foundation of competition-based accessibility measures, first derived in the general functional form by Weibull (1976), but introduced into practice by Shen (1998) when calculating mode-specific access to employment as a number of jobs normalized by the population that can reach them. Further advancements of this approach led to the introduction of several Floating Catchment Area (FCA) measures that account for both supply and demand within the service zones, like educational facilities or hospitals, while adjusting for overlapping areas (Paez et al., 2019; Pereira et al., 2021). This group of accessibility measures has been shown to provide more nuanced insights than cumulative metric into the disparities in access across different income groups stemming from transit time variability in Fortaleza, Brazil (Braga et al., 2026). Nevertheless, when Soukhov et al. (2023) revisited the mathematical proof presented by Shen (1998), they found a confounding of total population with people seeking opportunities and total number of opportunities with those actually in demand, and suggested an alternative approach, dubbed spatial availability, which relies on a proportional allocation mechanism akin to the spatial interaction model introduced by Wilson (1971). Unlike Shen's per capita measure, their approach results in the total number of opportunities available based on travel behavior and competition in the region, offering an intuitive interpretation since the units of opportunity (e.g., jobs) accessible by every origin add up to a total number of opportunities in the study region. Later on, the approach was further extended to account for competition between various transport modes (Soukhov et al., 2024).

2.2 Accessibility and travel behavior

There are strong theoretical underpinnings that explain accessibility's influence on travel behavior. Per Hägerstrand's (1970) space-time prism framework used by geographers, people's travel is guided by where and when they can go, given their ability, schedule, transport options, and time budget, with accessibility capturing interaction between those non-personal factors. On the other hand, from the RUT point of view promoted by the field of economics, users travel to destinations and via modes that provide them with the highest reward (Geurs & van Wee, 2004; Hasnine et al., 2019; Plevka et al., 2018). It should also be noted that measures of accessibility developed using RUM models overcome the limitations of discounting, competition, and interpretation (Geurs & van Wee, 2004) that other approaches mentioned above have, but they require the most detailed data inputs, usually collected through travel diaries, and are the most costly to compute.

Nevertheless, several researchers used cumulative accessibility to either control for transport and land-use interactions in their models, like the study of subjective well-being by Parga et al. (2024), or to predict travel behavior. Cumulative accessibility to jobs via transit has been shown to explain stop-level transit ridership (Dill et al., 2013) and PT mode share (Owen & Levinson, 2015), while Boisjoly and El-Geneidy (2016) found the static cumulative access measure calculated for 8 am to be representative of access at other times of the day and under dynamic PT schedule and employment scenarios in transit mode share models. At the same time, Cui et al. (2020) provided evidence that cumulative accessibility to jobs via transit impacts PT mode share for all income groups, but particularly for low-income ones, and Yousefzadeh Barri et al. (2021) confirmed this trend using gravity-based accessibility. Lastly, Negm and El-Geneidy (2024) confirmed that the positive relationship between accessibility and transit use remained valid even in the post-COVID-19 transit ridership recovery. All in all, these studies were consistent in the positive direction and effect size of accessibility's impact on transit use.

Another body of literature studied the explanatory power of various accessibility measures in travel behavior. Wu et al. (2019) compared the effect of transit job accessibility on transit mode share across 48 regions in the US using various thresholds for cumulative measure and five impedance functions for gravity-based measure. They found the exponential-square root form to offer the best fit, however the study focused on accessibility only, and did not control for any other factors known to impact mode share, as well as did not test competition-based measures. A study of transit stop choices in Greater Toronto Area compared the results of utility-based accessibility, a count of transit stops within 15-minute walking (i.e., cumulative access), and a gravity-based measure to find the latter two approaches to overestimate the access to transit compared to the former by including the stops that were infeasible from the point of final destination for the traveler (Hasnine et al., 2019). Nevertheless, their comparison was observational and did not include any statistical evaluation. On the other hand, Kim and Lee (2019) compared cumulative transit access to jobs at 40-, 50-, and 60-minute travel time thresholds, gravity-based access informed by an exponential decay function, and a Shen-like competition-based measure using a binary logit model for the Chicago region. They found the competition-based measure to introduce the highest descriptive power to the resulting choice model, with a 2.3 percentage point advantage over the gravity-based accessibility, and a 4.6 percentage point increase over the cumulative measure at 50-minute travel time. It should be noted, though, that the choices for the model were inferred from the Origin-Destination tract-level flows data, rather than individual-level source, suggesting that the differences should be treated with caution, as they might not be representative of the individual choices.

It is important to acknowledge that while accessibility impacts travel behavior and mode choice, it is not the only contributing factor that the literature has evidence on. Other characteristics were found to influence travel choices as well, like demographics and socioeconomic status (Ranjan & Sinha, 2025), trip context and transport system characteristics (Eluru et al., 2012), built environment (Ewing & Cervero, 2010), and preferences (Vij et al., 2013). In our analysis, we use available data to control for these characteristics while focusing on the impacts of accessibility measures of various functional forms.

As such, this study offers several contributions to existing literature. First, it compares the ability of non-competitive (cumulative, gravity-based) and competition-based accessibility measures (using two functional forms) to explain transit commute travel mode share. This effort provides evidence for the use of computationally efficient non-competitive accessibility measures for planning and evaluation purposes of travel behavior and access to opportunities that are not scarcely distributed. Secondly, following the established practice of accessibility applications in equity-focused transport research and planning (Iacono et al., 2008; van Wee & Geurs, 2011), the robustness of the findings is tested both for all incomes and for low-income households across three regions. The study ends with recommendations for policy and practice on the accessibility tool that professionals can use to achieve their planning goals.

3 Data

In this paper, we estimate transit accessibility to employment using cumulative, gravity-based, and competition-based frameworks and use them as predictors in regression analysis. We rely on jobs as a proxy for opportunities, since there is evidence that it captures not only the desirability of a place for workers, but also for the seekers of the services that employment provides, including entertainment, retail, hospitality, and other intangible goods (Deboosere & El-Geneidy, 2018; Owen et al., 2017). In this section, we discuss the details of the data sources and processing steps taken to prepare them for analysis.

3.1 Travel behavior and employment data

This study relied on the information available from the 2016 Canadian population census and commuting flows (CCF) (Statistics Canada, 2017) that provide counts of workers who commuted from their home census tract (CT) to their work CT, with the ability to disaggregate it by income and transport mode. Although Statistics Canada provides access to the 2021 census as well, we resorted to 2016 estimates since they were not affected by the COVID-19 pandemic when a significant portion of the workforce was traveling less and using their homes as an office. Similarly, despite CCF values available at a more disaggregate level of Dissemination Areas, potentially leading to higher spatial accuracy, it excludes significant portions of the region due to data suppression, making CTs a more appropriate unit of spatial analysis.

Knowledge about gross income was used to separately focus on workers in low-paying jobs, which were defined as those whose income was in the bottom 30% for the given region (Deboosere & El-Geneidy, 2018; Foth et al., 2013), which in the case of Toronto, Montreal, and Vancouver Census Metropolitan Areas (CMAs) was $CAD30,000 in 2016. Likewise, we relied on CCF data to calculate the shares of PT commuters at the CT level for all and low-wage workers. It should be noted that due to data suppression imposed by Statistics Canada to protect privacy (Statistics Canada, 2016) the actual values were not available for some income brackets for certain CTs which led to such discrepancies as the counts of total workers being different from the sum of all income groups for a given CT. Given that, we excluded CTs from the analysis where counts for low-income and non-low-wage categories could not be calculated. In the cases when we could calculate the number of workers in the non-low-wage category, we inferred the count for low-income category as a difference between the total number of workers and non-low-wage employees in a CT. Lastly, we removed any observations where transit mode share accounted for more than 80% of all low-income commuters, as these were found in CTs with data suppression issues and suspected to be inflated. This had minimal effect on the sample, removing about 1% of CTs in Toronto CMA, and about 3% of CTs in the two other CMAs. The information about employment was then used in accessibility calculations, while transit mode share was used as a dependent variable in the statistical models.

3.2 Transit travel time and quality data

Calculation of accessibility required the knowledge of travel times between the origins and destinations. To estimate it for transit, we relied on archived versions of General Transit Feed Specification (GTFS) data for October-November 2016 (based on the quality of GTFS feed) for Toronto, Montreal, and Vancouver CMAs, and processed them using r5r package (Pereira et al., 2021) to obtain the median travel time for the morning rush hour on a typical weekday for every CMA as the existing literature suggests (Boisjoly & El-Geneidy, 2016; Conway et al., 2018). These PT travel times include all components of the trip that apply to a particular origin-destination pair, like walking to and from transit stops, waiting, transfers, and in-vehicle time.

Another transit-related variable that we produced for the analysis was the distance to the nearest rapid transit, which could be either metro or commuter station, and bus rapid transit (BRT) stop. It was calculated as a network distance from the centroid of a CT to the nearest station/stop using dodgr package in R (Padgham, n.d.).

4 Methodology

In our analysis, we first calculated three types of accessibility measures, namely cumulative, gravity-based, and competition-based approaches, for every CMA. Cumulative accessibility was calculated for the average transit travel time in the region for the respective income category per recommendations in Kapatsila et al. (2023) using the classic equation from Hansen (1959):

$$A_i = \sum_j O_j f(C_{ij}),\ f(C_{ij}) = 1\ if\ C_{ij} \leq t, \text{ otherwise } f(C_{ij}) = 0 \qquad (1)$$

Where A_i stands for the accessibility of the origin CT i, O_j is the number of jobs at the destination CT j, C_{ij} captures the travel time between the origin and destination CTs, and $f(C_{ij})$ is the impedance function, which is equal to one when travel time is shorter than the set threshold (counting the destination CT as accessible), and zero otherwise.

Gravity-based accessibility was calculated using a Log-Logistic decay-cumulative density function due to its high correlation with the cumulative accessibility measure (Kapatsila et al., 2023). This choice was guided by the desire to focus primarily on the comparison of non-competitive and competition-based classes of accessibility measures, rather than compare alternative impedance functions. We empirically estimated decay parameter β from observed travel behavior by relying on non-linear least square methods with the Gauss-Newton algorithm embedded in the nls function in the stats package for R (R Core Team, 2013). Specifically, we generated an inverse cumulative density function from normalized cumulative share of observed trips at various travel times ranging from one to a hundred minutes. The parameter β was estimated by minimizing the sum of squared deviations between observed cumulative trip shares and model predictions. As such, the resulting impedance function $f(C_{ij})$ can be expressed in the following form:

$$f(C_{ij}) = \frac{1}{1 + (\frac{C_{ij}}{median(C)})^{\beta}} \qquad (2)$$

In other words, for every specific origin-destination pair, this impedance function acted as a weight for the number of jobs that could be reached. Likewise, this Log-Logistic decay-cumulative density function was used for the calculation of competition-based accessibility measures. Two approaches were considered. The first one was based on the method developed by Shen (1998), and incorporated competition for employment by dividing the supply of jobs at CT j by the total number of workers who can reach that CT. This relationship can be represented as follows:

$$A_i = \sum_j \frac{O_j f(C_{ij})}{D_j} \qquad (3)$$

where D_j is the total demand for employment at CT *j* (i.e., number of workers who can reach that CT), and it can be formulated as:

$$D_j = \sum_j P_{ij} f(C_{ij}) \tag{4}$$

where P_{ij} is the number of workers that can reach CT *j* from CT *i*.

Another approach to competition-based accessibility that we utilized in this study was spatial availability introduced by Soukhov et al. (2023) of the following functional form:

$$A_i = \sum_j O_j F_{ij}^t \tag{5}$$

where F_{ij}^t is the weighting factor that introduces the effect of competition and cost of travel in the system. As its definition implies, F_{ij}^t can be broken down into the population-based weight F_i^p and impedance-based weight F_{ij}^c that act as a joint probability of opportunities allocated to CT *i*:

$$F_{ij}^t = \frac{F_i^p F_{ij}^c}{\sum_j F_i^p F_{ij}^c} \tag{6}$$

Effectively, F_i^p is the proportion of population in CT *i* relative to the total population that ensures allocation of more jobs to more populated areas, and F_{ij}^c is the proportion of impedance between CTs *i* and *j* to total travel cost in the area, which assigns more opportunities to CTs that are nearby.

These accessibility to work measures estimated using equations above were used as independent variables in four multiple linear regression models that quantified their impact on the transit mode share in Toronto, Montreal, and Vancouver CMAs at the CT-level. We used the ordinary least squares method for estimation due to the ease of interpretation when exploring the relationship of variables and the irrelevance of bias that might have occurred if the estimates were to be used for prediction. Following the established econometric practice to capture increasing or diminishing effects of independent variables (Wooldridge, 2012), we also included a squared term for accessibility to account for the non-linear effect reported in past studies (Cui et al., 2020; Negm & El-Geneidy, 2024). This means that the size of the effect of accessibility on mode share was expected to change depending on the level of access, with an increase at high levels of accessibility offering lower marginal impact than at lower accessibility values.

The rest of the variables incorporated in the models were used for the control purpose. Specifically, we included information on CT-level demographics, like average age, median income, and mean household size. On the other hand, characteristics of the built environment were controlled for using population density and proximity to the nearest rapid transit stops (Ewing & Cervero, 2001). Lastly, we accounted for the effect of remote work on the share of transit riders by introducing the share of employees who work from home in a CT (Javadinasr et al., 2022). Summary statistics for the variables considered in the regression analysis are presented in Table 1.

Table 1. Descriptive statistics for the CTs in the three studied CMAs by mean (SD)

	Toronto		Montreal		Vancouver	
Region Population (2016)	5,928,040		4,104,074		2,463,431	
Number of CTs in Analysis	N= 1140		N= 944		N= 463	
	All Commuters	Low income	All Commuters	Low income	All Commuters	Low income
Transport Mode Share						
Public transit mode share (%)	32.14 (17.54)	23.68 (13.66)	31.43 (18.48)	23.31 (14.06)	28.75 (13.87)	16.87 (10.14)
Car mode share (%)	55.8 (22.19)	70.24 (19.44)	53.83 (24.64)	67.84 (21.44)	56.98 (19.08)	74.35 (17.03)
Accessibility measures						
Cumulative opp. [x10,000]	19.35 (24.16)	5.48 (6.18)	22.19 (26.03)	6.43 (7.75)	13.59 (14.52)	4.09 (4.29)
Gravity-based [x10,000]	24.38 (24.08)	6.67 (6.36)	24.26 (22.67)	7.25 (6.93)	14.16 (12.7)	4.32 (3.85)
Shen-type	1.13 (2.33)	1.14 (2.06)	1.16 (1.01)	1.29 (1.07)	1.24 (3.68)	1.41 (6.21)
Spatial availability [x10,000]	0.22 (0.44)	0.07 (0.12)	0.18 (0.17)	0.07 (0.06)	0.22 (0.26)	0.07 (0.07)
CT characteristics						
Employed population (%)	60.81 (7.09)		61.07 (8.23)		61.28 (7.56)	
WFH employees (%)	7.42 (3.96)		6.9 (3.1)		8.56 (4.4)	
Age	40.27 (3.95)		40.65 (4.25)		41.38 (4.01)	
Household	2.84 (0.6)		2.31 (0.41)		2.65 (0.56)	
Median income	8.56 (3.08)		6.6 (2.67)		7.84 (2.16)	
Population density (1,000/km2)	5.59 (6.44)		5.67 (5.19)		4.69 (4.95)	
Distance to RTS (km)	3.7 (4.98)		4.59 (6.03)		6.05 (6.07)	

Given the spatial nature of the data, we calculated Moran's I (Moran, 1950) on the residuals of every model to identify the potential bias coming from the spatial autocorrelation. Since it was found to be statistically significant, we relied on the Conley standard errors when identifying the relevance of the variables, which is a type of robust error that overcomes the bias coming from heteroskedasticity and spatial dependency (Conley, 1999). When defining the cutoff value for calculating Conley standard errors, we relied on 2, 5, and 10-kilometer thresholds to account for varying sizes of CTs, however did not see a significant difference in the results. As such, the reported confidence intervals are based on the 5-kilometer cutoff distance in the final tables.

5 Results

In this paper, we perform a comparative analysis of three types of accessibility to employment, using cumulative, gravity-based, and competition-based approaches. To get the base understanding of the patterns, we first explored the relationship between PT mode share and access to jobs visually. An illustrative example for Toronto is presented in Figure 1. It is easy to notice the overlap in patterns of high access between cumulative and gravity-based accessibility with larger shares of transit use. Spatially, these are more prevalent around the central core of the Toronto region, where many of its rapid transit lines overlap. At the same time, for competition-based measures, only suburban CTs stand out in terms of higher-than-average level access, where transit mode share is low.

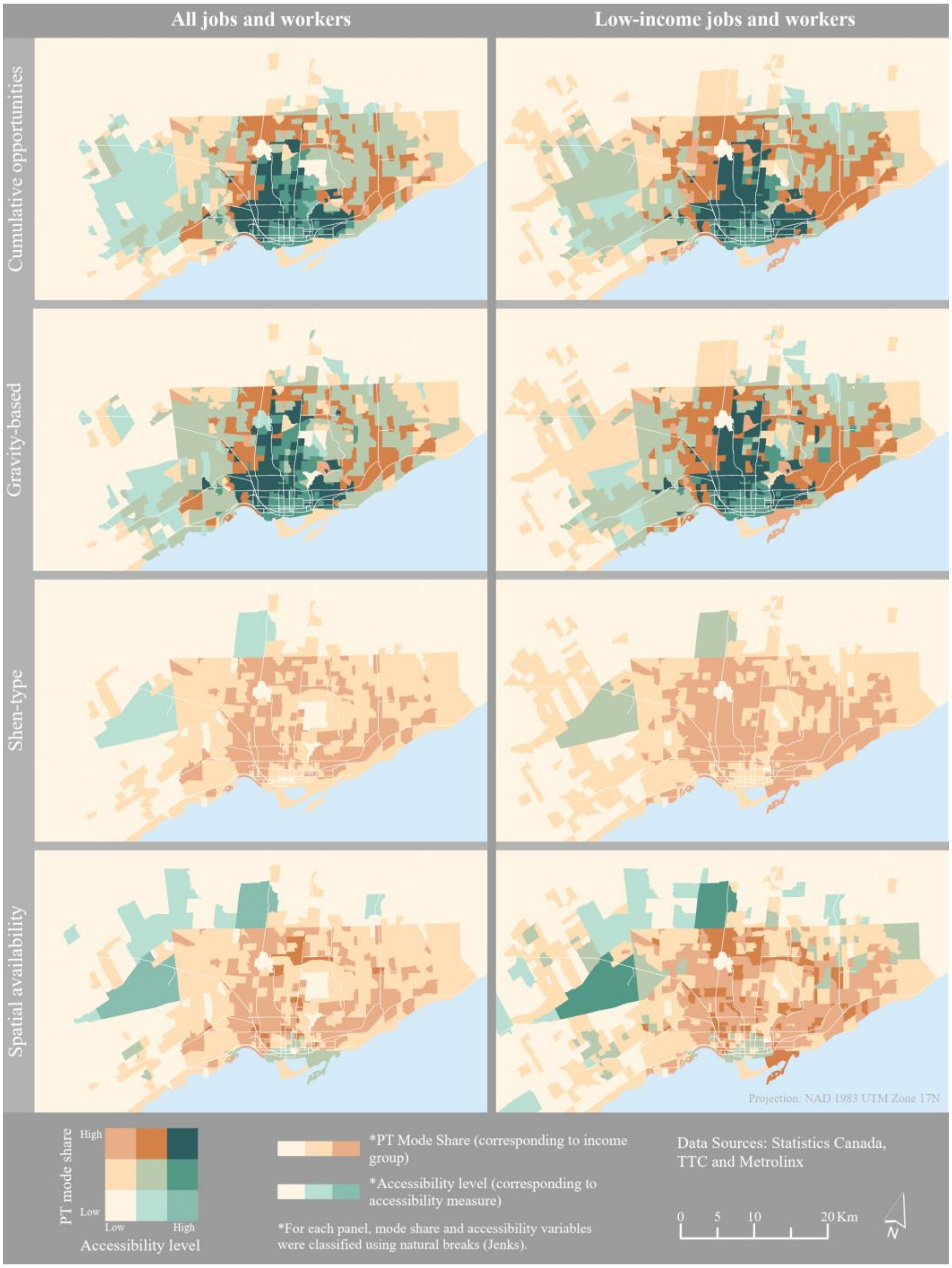

Figure 1. Toronto accessibility and public transit mode share for all and low-income workers

Next, we performed regression analysis to compare the explanatory power of association of different accessibility to jobs measures and travel behavior, particularly the choice of transit for commuting to work. The share of transit commuters in a CT was used as a dependent variable, and we iteratively tested the performance of every model with cumulative accessibility at the mean travel time in the region, gravity-based accessibility, Shen-type measure, and spatial availability measure for all, and low-income jobs in Toronto, Montreal, and Vancouver regions, while controlling for demographic parameters and characteristics of transit systems and built environment. A total of 24 models were estimated. We provide the models' results for all jobs in Toronto CMA in Table 2, and for low-wage jobs in Table 3, and a comparison of coefficients of determination (R^2) for all models in Table 4. The detailed results for Montreal and Vancouver are available in the appendix.

Table 2. Toronto public transit mode share percentage regression models for all commuters

Predictors	Model 1A Cumulative opp. [x10,000] (Mean TT)		Model 2A Gravity-based [x10,000] (Fisk decay parameter)		Model 3A Shen-type (Log-Logistic decay parameter)		Model 4A Spatial availability [x10,000] (Log-Logistic decay parameter)	
	Coef.	95% CI	Coef.	95% CI	Coef.	95% CI	Coef.	95% CI
Intercept	39.54 **	11.91 – 67.16	37.69 **	14.80 – 60.58	73.53 ***	42.91 – 104.15	78.91 ***	47.17 – 110.65
Accessibility								
Accessibility measure	0.91 ***	0.61 – 1.20	0.73 ***	0.54 – 0.92	1.90 ***	0.77 – 3.02	-2.42	-10.64 – 5.80
Accessibility measure squared	-0.01 ***	-0.01 – -0.00	-0.01 ***	-0.01 – -0.00	-0.03 ***	-0.05 – -0.01	0.21	-0.56 – 0.98
CT Population characteristics								
WFH employees (%)	-0.73 **	-1.17 – -0.29	-0.49 **	-0.83 – -0.16	-0.63 **	-1.10 – -0.15	-0.62 *	-1.10 – -0.14
Age (avg)	-0.15	-0.60 – 0.31	-0.27	-0.64 – 0.10	-0.41	-0.86 – 0.05	-0.41	-0.86 – 0.03
Household size (avg)	-3.87 *	-7.29 – -0.45	-2.85 *	-5.45 – -0.26	-9.78 ***	-13.79 – -5.78	-10.82 ***	-15.02 – -6.63
Built environment								
Population density (1000/km^2)	0.26 **	0.07 – 0.44	0.27 ***	0.13 – 0.41	0.54 **	0.20 – 0.88	0.58 ***	0.25 – 0.90
Distance to Station (km)	-0.47 ***	-0.62 – -0.32	-0.40 ***	-0.52 – -0.27	-0.82 ***	-1.06 – -0.58	-0.84 ***	-1.09 – -0.59
Observations	1140		1140		1140		1140	
R2 / R2 adjusted	0.658 / 0.655		0.690 / 0.688		0.490 / 0.487		0.477 / 0.474	

‾ The accessibility measure corresponds to the Model name

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table 3. Toronto public transit mode share percentage regression models for low-income commuters

	Model 1L		Model 2L		Model 3L		Model 4L	
Predictors	Cumulative opp. [x10,000] (Mean TT)		Gravity-based [x10,000] (Log-Logistic decay parameter)		Shen-type (Log-Logistic decay parameter)		Spatial availability [x10,000] (Log-Logistic decay parameter)	
	Coef.	95% CI	Coef.	95% CI	Coef.	95% CI	Coef.	95% CI
Intercept	50.75**	16.11 – 85.40	50.30***	22.55 – 78.04	93.73***	57.66 – 129.81	97.89***	60.71 – 135.06
Accessibility								
Accessibility measure	4.77***	3.78 – 5.76	3.81***	3.15 – 4.48	1.61***	0.67 – 2.56	-8.18	-34.93 – 18.57
Accessibility measure squared	-0.17***	-0.22 – -0.12	-0.12***	-0.15 – -0.08	-0.03**	-0.05 – -0.01	3.17	-6.12 – 12.45
CT Population characteristics								
WFH employees (%)	-0.99***	-1.38 – -0.59	-0.75***	-1.07 – -0.43	-1.06**	-1.75 – -0.38	-1.06**	-1.75 – -0.36
Age (avg)	-0.29	-0.86 – 0.28	-0.41	-0.85 – 0.03	-0.48	-1.00 – 0.05	-0.47	-1.01 – 0.06
Household size (avg)	-4.60*	-8.92 – -0.28	-3.87*	-7.11 – -0.64	-12.32***	-17.10 – -7.54	-13.13***	-17.99 – -8.27
Built environment								
Population density (1000/km²)	0.06	-0.13 – 0.25	0.10	-0.07 – 0.26	0.42	-0.01 – 0.86	0.45*	0.03 – 0.87
Distance to Station (km)	-0.42***	-0.59 – -0.25	-0.37***	-0.53 – -0.22	-0.97***	-1.28 – -0.66	-0.97***	-1.28 – -0.66
Observations	1140		1140		1140		1140	
R2 / R2 adjusted	0.653 / 0.650		0.671 / 0.669		0.417 / 0.413		0.412 / 0.408	

¯ The accessibility measure corresponds to the Model name
* p<0.05 ** p<0.01 *** p<0.001

Given the aggregate nature of cumulative, gravity-based, and spatial availability measures, their values were divided by 10,000 in the regression models, to ensure consistency with the Shen-type accessibility, which is a per-capita measure. Table 2 reveals that for all incomes in Toronto, cumulative, gravity-based, and Shen-type measures have a positive impact on PT mode share, while the spatial availability measure is not statistically significant. Furthermore, examination of the coefficients of determination suggests that the spatial availability measure only adds noise to the model, with both its R2 and R2 adjusted being the lowest among all four measures. At the same time, gravity-based measure offers the best model fit, with about 69% of variance explained by the model in total, and cumulative accessibility coming in second, lagging only by a little more than two percentage points.

Looking at the model fit results for Montreal and Vancouver in Table 4, we largely see confirmation of the observed trend. While the models for all incomes in the latter two regions see spatial availability as statistically significant, both competition-based accessibility measures offer the poorest explanatory power. The cumulative opportunities measure introduces the best fit in Vancouver, though the improvement over gravity-based access is within the two percentage point range. This finding is different from the comparison in Kim and Lee (2019), who found the performance of Shen-type access to offer the best model fit, followed by gravity-based and cumulative measures, though only by 2.3 and 4.6 percentage points, respectively. This discrepancy likely stems from the fact that they focused on the 50-minute threshold for cumulative access, rather than the average regional transit travel time of 29 minutes (Kim & Lee, 2019). Likewise, Log-

Logistic decay-cumulative density function was not explored for gravity-based measures in that study, which was reported to be highly correlated with the cumulative accessibility estimated for the mean travel time in the literature (Kapatsila et al., 2023).

Table 4. Coefficients of determination (R^2) for multiple linear regressions with public transit mode share as the dependent variable

Census Metropolitan Region	N	Accessibility measure			
		Cumulative opp. [x10,000] (Mean TT)	Gravity-based [x10,000] (Log-Logistic decay parameter)	Shen-type (Log-Logistic decay parameter)	Spatial availability [x10,000] (Log-Logistic decay parameter)
		R2 / R2 adj.	R2 / R2 adj.	R2 / R2 adj.	R2 / R2 adj.
Toronto (All commuters)	1140	0.658 / 0.655*	0.690 / 0.688*	0.490 / 0.487*	0.477 / 0.474
Toronto (Low-income)	1140	0.653 / 0.650*	0.671 / 0.669*	0.417 / 0.413*	0.412 / 0.408
Montreal (All commuters)	944	0.768 / 0.767*	0.794 / 0.792*	0.683 / 0.681*	0.657 / 0.655*
Montreal (Low-income)	944	0.709 / 0.706*	0.750 / 0.749*	0.588 / 0.585	0.580 / 0.577
Vancouver (All commuters)	463	0.718 / 0.714*	0.693 / 0.688*	0.548 / 0.541	0.561 / 0.555*
Vancouver (Low-income)	463	0.674 / 0.669*	0.644 / 0.638*	0.453 / 0.444	0.491 / 0.483*

* Statistically significant accessibility measure
Each model controls for average age, average household size, and work from home % in the CT, in addition to the population density in the CT and CT centroid's distance to closest rapid transit station.

Following the prevailing practice in the literature, we also capitalize on accessibility's ability to shed light not only on the general societal impact of transport and land-use systems, but also on the vulnerable populations (Levinson, 2002). Table 3 reports the results of regression analysis for PT mode share for low-income workers using accessibility estimates to low-income jobs in Toronto CMA. The estimates follow the same trend as observed for all jobs in Table 2, with the spatial availability measure being not statistically significant and the model with that measure offering the poorest fit. Looking at results for low-income jobs in Montreal and Vancouver in Table 4, we can see that the latter region is the only one where the Shen-type measure is not statistically significant, while the spatial availability measure is. Nevertheless, the two competition-based measures still offer the lowest explanatory power when predicting transit mode share for low-wage workers. All in all, our models suggest that across the three studied regions and for both all and low-income groups, the use of cumulative access measure is not dramatically inferior to gravity-based ones (within two-four percentage points), or better, as in the case of Vancouver, and it is consistently superior to competition-based measures, by at least ten percentage points.

Some explanation can be offered to understand the inferior performance of competition-based measures. First of all, one should reflect on the nature of the opportunity selected for the analysis. While, naturally, people compete for positions when they are seeking employment, it is no longer the case when they get it and have to travel to work, making employment centers more attractive destinations due to the sheer number of jobs. This competition translates into some of the transit lines being crowded at peak demand, affecting people's travel time and mode choices (Kapatsila et al., 2025), but it does not make them travel elsewhere. Likewise, when it comes to services that make places more attractive to travel to, we know from economics and communication studies that people tend to place higher value on those opportunities that are more in demand, perceiving them as having superior value. For example, Banerjee (1992) found that people have a tendency to mimic the choices of those who acted before them, foregoing their own private knowledge, while Katz and Lazarsfeld (1955) observed this broad effect of communication coming from opinion leaders. At the same time, Kahneman et al. (2022) discuss how social influence undermines the rationality of individual choices. In other words, this research suggest that there are instances when higher competition for a certain good may facilitate people's desire to engage with it.

All in all, from the transit mode share perspective, accounting for competition in accessibility assessment in general transport plan evaluation does not generate improvements or benefits, both from a conceptual and statistical point of view, especially given the additional implementation efforts required for that. In line with findings of Kapatsila et al. (2023), we arrive at the conclusion that the cumulative accessibility measure calculated for the average regional travel time is a reliable metric for the assessment of transport and land-use interactions and its association with travel behavior, while requiring fewer data inputs and processing efforts. At the same time, we want to underscore the value of competition-based measures and recommend their use in special cases, where scarce resources are present and the demand is high, for example, access to hospital beds (Boisjoly et al., 2020).

In this analysis, we focus less on the interpretation of the effects of control variables, given their performance, which is consistent with that reported in the previous literature. The quadratic term, which captures the additional effect of accessibility to jobs, is negative as it was also found in Negm and El-Geneidy (2024), suggesting that the positive effect of access is non-linear and wears off after reaching a peak. When it comes to other demographic variables, an expected decline in transit mode share with age confirms the estimates available in past studies (Brown et al., 2016; Newbold & Scott, 2018), while it is not surprising that areas with higher shares of remote workers result in lower transit mode share among commuters (Carvalho & El-Geneidy, 2024). Likewise, the effect of household size is negative, which corresponds with the knowledge that parenthood tends to lead to vehicle purchases and more driving (Jamal & Newbold, 2020), and a decline in transit use as a result.

The last group of variables that we controlled for aimed to capture the effect of the built environment on travel behavior. Density has an expected positive effect among all four models for all incomes in Toronto, as is well-documented in past studies (Cervero & Kockelman, 1997; Ewing & Cervero, 2001; Zahabi et al., 2016). Nevertheless, it is only statistically significant in combination with Shen-type and spatial availability opportunity measures for low-wage workers. This difference can likely be explained by the usual correlation that exists between low income and high population density in North American cities (Lens & Monkkonen, 2016) that is captured in aggregate accessibility measures, but is less prevalent once accessibility estimates are normalized by demand, as it is in spatial availability and the Shen-type measure. At the same time, all models consistently captured the negative effect of distance increase to rapid transit infrastructure (Cervero et al., 2010). On the whole, these control variables support the validity of the estimated models, given the confirmation of their analytical rigor.

6 Conclusions

This study compared the degree of association of cumulative, gravity-based, and competition-based opportunity measures and travel behavior, measured by the share of transit mode users at the CT-level, in Toronto, Montreal, and Vancouver, Canada. Our findings are in line with the existing literature that previously reported a positive association between accessibility measures to jobs and PT mode share and identified that the cumulative access measure calculated at the mean travel time in the region and the gravity-based measure result in higher explanatory power of the statistical models than when using competition-based measures. Moreover, the relatively low difference between models with cumulative and gravity-based accessibility speaks in favor of the reliability of cumulative accessibility in the assessment of transport impacts on travel mode share, though the difference might have been more pronounced if other specifications for the gravity-based measure were tested. Our analysis demonstrated consistent results across different geographies and remained largely unchanged when we repeated estimations for low-wage jobs only. Accordingly, our study recommends the use of the cumulative opportunities accessibility measure at the mean travel time in a region in planning practice, due to its reliability, ease of calculation, and ease of communication.

The implications of the study are twofold. On one hand, we contribute to the evolving argument that advocates for the broader adoption of cumulative accessibility by practitioners, due to its relatively low demands for data inputs, technical skills of analysts, and straightforward interpretation (compared to other approaches). In line with the evidence from previous studies (El-Geneidy & Levinson, 2006; Geurs, 2020; Kapatsila et al., 2023; Tomasiello et al., 2023), we provide justification that more complex accessibility measures, particularly competition-based measures, should be considered by analysts in instances when competition for limited resources is an operative component. The overall hope is for the findings to endorse the broader adoption of the cumulative accessibility metric for performance-based transport planning and evaluation. At the same time, the need to further explore the use case of competition-based accessibility measures is apparent. While our findings endorse the use of cumulative-based accessibility measures for general planning purposes, the cases of rivalry opportunities, and their impact on travel choices, especially in the context of emergencies, like hospital beds and shelter spaces, require further exploration.

Overall, with this paper, we enhance the argument in favor of the adoption of simple accessibility measures for the task of predicting behavioral changes and assessing land use and transport impacts in planning projects in the North American context. It should be acknowledged that performing the analysis at the Census Tract level provided insights for aggregate associations and might not directly translate to individual travel behavior. The effect might be more prominent for suburban parts of the studied regions, where Census Tracts tend to be larger, and thus are subject to spatial variation in transit accessibility. Furthermore, due to the ecological fallacy phenomenon, the patterns observed at the group level might obfuscate some individual choices and should be further explored in future studies with more granular data. At the same time, while the 2016 Census data was acceptable for the comparison of different methods across various regions, it is important that more recent data sources are used by practitioners for actual planning purposes. As such, future research can explore the potential differences in other contexts, for active transport modes, and for other segments of the population, as well as using enhanced data sources, like stated and revealed preference surveys analyzed using a discrete choice modeling framework.

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Author contribution

The authors confirm their contribution to the paper as follows: study conception and design: A. El-Geneidy, B. Kapatsila, and H. Negm; data collection: B. Kapatsila and H. Negm; analysis and interpretation of results: A. El-Geneidy, B. Kapatsila, and H. Negm; draft manuscript preparation: A. El-Geneidy, B. Kapatsila, and H. Negm. All authors reviewed the results and approved the final version of the manuscript.

Appendix

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