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Walkability indices and travel behavior: Insights from Montréal, Canada

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Abstract: Walkability indices are developed to evaluate the quality of the built environment and its suitability for walking. Over the past decade, several walkability indices were developed and promoted by public and private entities around the world. Comparing and validating these indices are essential to ensuring their reliability for adoption in practice. One method to validate such indices is to examine their predictive power for utilitarian and discretionary walking behavior. This study uses data from a large-scale travel survey (N=4,715), conducted in Montréal, Canada, to examine the predictive power of six region-specific walkability indices on weekly walking mode share for various purposes, namely work, school, shopping, leisure, and healthcare. We find that the Canadian Active Living Environments (Can-ALE) index and its extended version, Can-ALE/Transit, are the best predictors of overall weekly walking mode share for all purposes combined, shopping, and leisure activities. Walk Score® had the highest predictive power on walking behavior for healthcare purposes. While the cumulative opportunities measure (30-minute travel time) was the most effective for predicting commute walking behavior. This research provides valuable insights for practitioners and policymakers, guiding them in selecting the most suitable walkability indices to promote walking behavior in the Canadian context.

Keywords: walkability, index, travel behavior, shopping, North America

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1 Introduction

The concept of walkability has been gaining attention with the growing interest in designing x-minute cities (e.g., 15, 20, 30 minutes), where all essential destinations are accessible by active travel (Logan et al., 2022; Lu & Diab, 2023; Teixeira et al., 2024). Over the last decade, various indices have been developed and promoted by public and private organizations to assess the quality of the walkable environments (Vale et al., 2015). Walkability indices usually focus on factors such as population and activity density, land-use and destinations diversity, and overall design quality (Ewing & Cervero, 2010; Ewing & Handy, 2009). These walkability indices have been found reliable in predicting the impact of the built environment on physical activity (Hino et al., 2022; Stockton et al., 2016), travel behavior (Lefebvre-Ropars & Morency, 2018;

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Manaugh & El-Geneidy, 2011), and health outcomes (Frank et al., 2006; Rundle et al., 2019; Sallis et al., 2009; Yang et al., 2021). Given the numerously generated walkability indices and the ever-changing built environment, the ongoing validation and assessment of the reliability of these walkability indices in predicting walking behavior is crucial for their practical application.

Walkability can be measured objectively by analyzing the components of the built environment or subjectively (i.e., perceived walkability) through surveys that assess how easy people find it to walk in an area or to reach destinations (De Vos et al., 2023; Saelens et al., 2003). Many studies found an alignment between objective and perceived walkability (Arvidsson et al., 2012; Gebel et al., 2009), reinforcing the importance of objective walkability indices as predictors of physical activity and walking behavior. Since objective walkability indices are often developed using localized data at the city or national level, they require corresponding survey data on travel behavior at the same level to ensure their validity. While multiple studies have found that objective walkability indices are significantly related to walking behavior, as measured through surveys (Christian et al., 2011; Frank et al., 2006; Lam et al., 2022)—particularly non-recreational walking (Saelens & Handy, 2008)—few have compared walkability indices and investigated which are best in predicting walking behavior (Lefebvre-Ropars & Morency, 2018; Manaugh & El-Geneidy, 2011; Shashank & Schuurman, 2019).

In Montréal, Canada, two studies tested this impact using a local Origin-Destination survey, a dataset limited by participants only reporting their trips from the previous day and therefore not capturing the overall picture of an individual's travel behavior (Lefebvre-Ropars & Morency, 2018; Manaugh & El-Geneidy, 2011). While these studies relied on calculating previously proposed walkability indices from scratch to suit the purpose of the research, they tested the validity of Walk Score®, a readily available index, and found it comparable to other complex measures (Manaugh & El-Geneidy, 2011). Recently, a number of walkability indices have become accessible in Canada (Ross et al., 2018; Statistics Canada, 2023b), eliminating the need to perform complex calculations. These indices are yet to be validated as predictors of walking travel behavior, which is essential for their effective implementation in practice.

This research aims to assess the reliability of six walkability indices in explaining observed utilitarian and discretionary walking behavior. Using data from the fourth wave of the Montréal Mobility Survey (MMS) conducted in Fall 2023 in Montréal, Canada (Victoriano-Habit et al., 2024), we run multiple linear weighted regressions on 4,715 participants to estimate the impact of different walkability indices on weekly walking mode share for five different destinations. We then run separate models to explore the predictive efficiency of certain measures for a specific purpose. This research provides valuable insights for practitioners and policymakers, guiding them in selecting the most suitable walkability indices to promote walking behavior in the Canadian context.

2 Literature review

Walking is impacted by a range of subjective and objective determinants (Aziz et al., 2018; Panter & Jones, 2010; Scheiner & Holz-Rau, 2007; Ton et al., 2019). The built environment is one of the most prominent objectively measured attributes that influence walking behavior (Cervero, 2002; Rodríguez & Joo, 2004; Saelens & Handy, 2008). Environments with high activity density, diverse land uses, comfortable design, accessible destinations, and short distances to transit are deemed walkable (Ewing & Cervero, 2010). To study the quality of the built environment and its impact on travel behavior, many walkability indices have been developed that consider the various aspects of the built environment (Krambeck, 2006; Kuzmyak et al., 2005).

Walkability indices often rely on localized data, such as the number of accessible amenities, making them context specific (Giles-Corti et al., 2014; Shashank & Schuurman, 2019). Some examples are city-level indices that have been developed and validated in Sydney (Mayne et al., 2013), London (Stockton et al., 2016), and Yokohama, Japan (Hino et al., 2022). In all three studies, the authors found a correlation between the index and walking behavior depicted in distance and time, where people living in areas with higher scores tend to walk more. Other indices have been developed and tested on a nation-wide scale, such as the National Walkability Index developed in 2017 in the US, which was found to be associated with a higher likelihood of walking, especially for leisure and to public transport in urban areas (Watson et al., 2020). It is not uncommon for the same regions to develop different walkability indices. A few years after the National Walkability Index was launched, Rundle et al. (2019) developed the Built Environment and Health-Neighborhood Walkability Index (BEH-NWI) to measure neighborhood walkability in the US, which was found to be associated with self-reported walking per week and body mass index. Similarly, a walkability index developed by Lam et al. (2022) for the Netherlands was found to be associated with adults walking behaviors.

One of the publicly operationalized indices on a large scale is Walk Score (Walkscore.com), available in the United States, United Kingdom, Canada and Australia. Such a freely available tool allows users to examine neighborhood walkability based on proximity to different amenities which helps in residential selection and real estate valuation. A study by Carr et al. (2011) showed Walk Score as a reliable measure for estimating areas with a high density to walkable amenities. In Montréal, Manaugh and El-Geneidy (2011) found Walk Score to be comparable in predicting non-work walking trips to other walkability indices, such as the ones developed and/or used by Kuzmyak et al. (2005) and Porta and Renne (2005). Another study in Montréal, conducted by Lefebvre-Ropars and Morency (2018), examined the correlation between four walkability measures and the choice of walking for short trips. The four measures were the Pedestrian Index of the Environment (PIE), the Walkability Index (WI), the Pedestrian Potential Index (PPI) and the Neighborhood Destination Accessibility Index (NDAI). They found that each of the indices has its strength and limitations in predicting trips for certain purposes and various spatial levels.

To our knowledge, newly developed walkability indices for Canada, such as the Canadian Active Living Environments (Can-ALE) (Herrmann et al., 2019; Ross et al., 2018) and Spatial Access Measures (Statistics Canada, 2023b), have not been compared to more established measures, such as the Walk Score, as predictors of walking. This research aims to fill this gap by examining the reliability of six different context-specific walkability indices (Walk Score, Spatial Access Measures, Can-ALE, Can-ALE/Transit and cumulative opportunities accessibility within 15 and 30 minutes) in estimating utilitarian and discretionary walking behavior.

3 Data and methods

3.1 Survey data

This study uses data from the fourth wave of the Montréal Mobility Survey (MMS), conducted in Fall 2023. MMS is a bilingual longitudinal online survey that collects sociodemographic characteristics, attitudes towards transit, current and past travel behavior, and physical activity from residents in Montréal, Canada (Victoriano-Habit et al., 2024). A thorough validation process enforced a set of exclusion criteria to eliminate unreliable responses. This process used participants' e-mail and IP addresses, the time they took to fill out the survey, the location pins or addresses they indicated for home, work and/or school, household structure, and age and height data for participants who filled out previous waves of the MMS. Any incomplete responses were dropped. Survey entries that were filled from the same IP address or with the same email address were removed from the valid responses. As participants get different sets of questions based on their answers in previous sections, this results in different groups of respondents. For each group, surveys in the top 5% in speed of completion were dropped. This threshold was determined by analyzing the distribution of response times to identify outliers. When plotting all response times in cumulatively, a noticeable change in the slope was observed around the 5th percentile, indicating a natural cut-off point. Observations were removed if the home location was missing, or if the home, work, or school locations reported by participants were outside the Montréal Census Metropolitan Area (CMA) or were invalid (e.g., located on water). Individuals with inconsistent household data were eliminated (e.g., the number of adults exceeds the total household size). For participants who responded to previous survey waves, observations were dropped if there were implausible changes in age or height. For participants who chose not to disclose their income level, this missing data was imputed using Multivariate Imputation by Chained Equations (MICE) via the R package mice (van Buuren & Groothuis-Oudshoorn, 2011). The imputation process incorporated variables such as age, gender, employment status, household composition, and education. The fourth wave's recruitment resulted in a total of 5,277 complete and valid responses.

In this study, we utilize questions about home locations, travel behavior, travel identity, residential self-selection, and socioeconomic characteristics. For travel behavior, we use the number of trips that the participants performed per week for work, school, shopping, healthcare, and leisure and the travel mode they used for these trips. There were four main travel mode categories: car, transit, walking, and cycling. To account for travel identity, participants were asked to identify the travel mode they associate themselves with. They were provided with the option to choose multiple modes (e.g., I consider myself a driver and a pedestrian). For residential self-selection, participants were asked to indicate the importance of living in a neighborhood where it is pleasant to walk when they selected their current residence. Socioeconomic characteristics included gender, age, household composition, income level, and number of accessible cars. Based on the distribution of the data, we only maintained participants whose weekly trip count fell within the range of four to thirty trips as we consider them mobile people with a reasonable number of trips for whom we can reliably calculate mode share percentages. This filtering resulted in a final sample of 4,715 participants who performed trips for at least one of the five purposes examined.

3.2 Walkability indices

We examine six walkability indices: Walk Score, Spatial Access Measures, Can-ALE, Can-ALE/Transit and cumulative opportunities accessibility within 15 and 30 minutes of walking. Out of these six measures, only Walk Score can be considered non-specific to Canada as it is used to estimate walkability in many other regions. Meanwhile, the other five indices are designed specifically for the Canadian context.

Walk Score is a proximity gravity-based measure that evaluates access to 13 different amenities within walking distance and provides a score from 0 (car-dependent) to 100 (walker's paradise) (Walk Score, 2024b). It was collected following the survey's collection (Fall 2023) based on each participant's home location using the Walk Score API (Walk Score, 2024a). The Spatial Access Measures are developed by Statistics

Canada (2023b) in collaboration with Infrastructure Canada. They are gravity-based measures, measuring the access to seven types of amenities for four modes of transport on the dissemination block (DB) level, with each index ranging between 0 and 1. For this study, we use the index for access to places of employment by walking, as this is the most comprehensive and suitable for our objective. This research utilized the latest index update from August 2023.

The Can-ALE is a measure of the active-living friendliness of an area, comprising three components: dwelling density, number of connected intersections, and number of destinations (Herrmann et al., 2019; Ross et al., 2018). The Can-ALE/Transit is an extended version of the Can-ALE, which integrates transit stops as a fourth component. For Can-ALE and Can-ALE/Transit, the index represents the sum of the z-values for the three and four components' measures, respectively, measured at the dissemination area (DA) level of analysis. The latest version of the index was developed using 2017 geographic data and 2016 census data.

The emergence of the 15-minute city concept over the past five years has placed access to jobs and other destinations by walking at the forefront of research on mode choice (Birkenfeld et al., 2023; Logan et al., 2022; Lu & Diab, 2023). Therefore, we include accessibility to jobs by walking as a potential walkability index. The local accessibility by walking was calculated using the 2016 Canadian commuting flows (CCF) (Statistics Canada, 2017). The CCF tables provide the number of workers commuting between their home and work census tracts (CT). While this data is available for 2021, many jobs relied entirely on telecommuting due to the COVID-19 pandemic, which may not accurately reflect the current situation. We decided that using the 2016 CCF tables would provide a more representative depiction of the present circumstances, as many areas have since restored to pre-pandemic activity despite the ongoing prevalence of telecommuting (Anik & Habib, 2023; Javadinasr et al., 2022). Using this dataset, we identify the number of jobs available in each CT, which is then distributed proportionally by area to the DAs that constitute the CT. The OpenStreetMap street network was obtained for the Montréal Census Metropolitan Region (CMA) through BBBike extracts which was then used in the r5r package in R to calculate a travel time matrix (TTM) between DA centroids (Pereira et al., 2021). Based on the TTM, we determined the cumulative opportunities accessibility measure with 15 and 30 minutes as the travel time thresholds with a walking speed of 3.6 km/h (2.2 miles/h) (Pereira et al., 2021).

In Figure 1, each map presents the distribution of the z-score values for its responding index and geographical unit across the Montréal region. All measures were available for the region of Montréal according to their geographical unit, except for Walk Score as it was retrieved for each participants' address. For visualization purposes, it was retrieved for every postal code in the region. Each index was standardized and displayed in equal intervals. The maps show stark contrasts in data distribution, both within and between each map. Walk Score displays an abundance of high scores in the urban core and sub-core areas. Spatial Access Measures, Can-ALE and Can-ALE/Transit data have a rather similar distribution where the downtown area has the highest scores, which start to fade moving outwards of the urban core. The cumulative opportunities measures display a highly skewed distribution. This is due to the DA, the geographical unit used for this measure, having a smaller area around downtown in addition to the abundance of jobs in this zone. As a result, job accessibility by walking is exponentially higher near the urban core compared to the rest of the region.

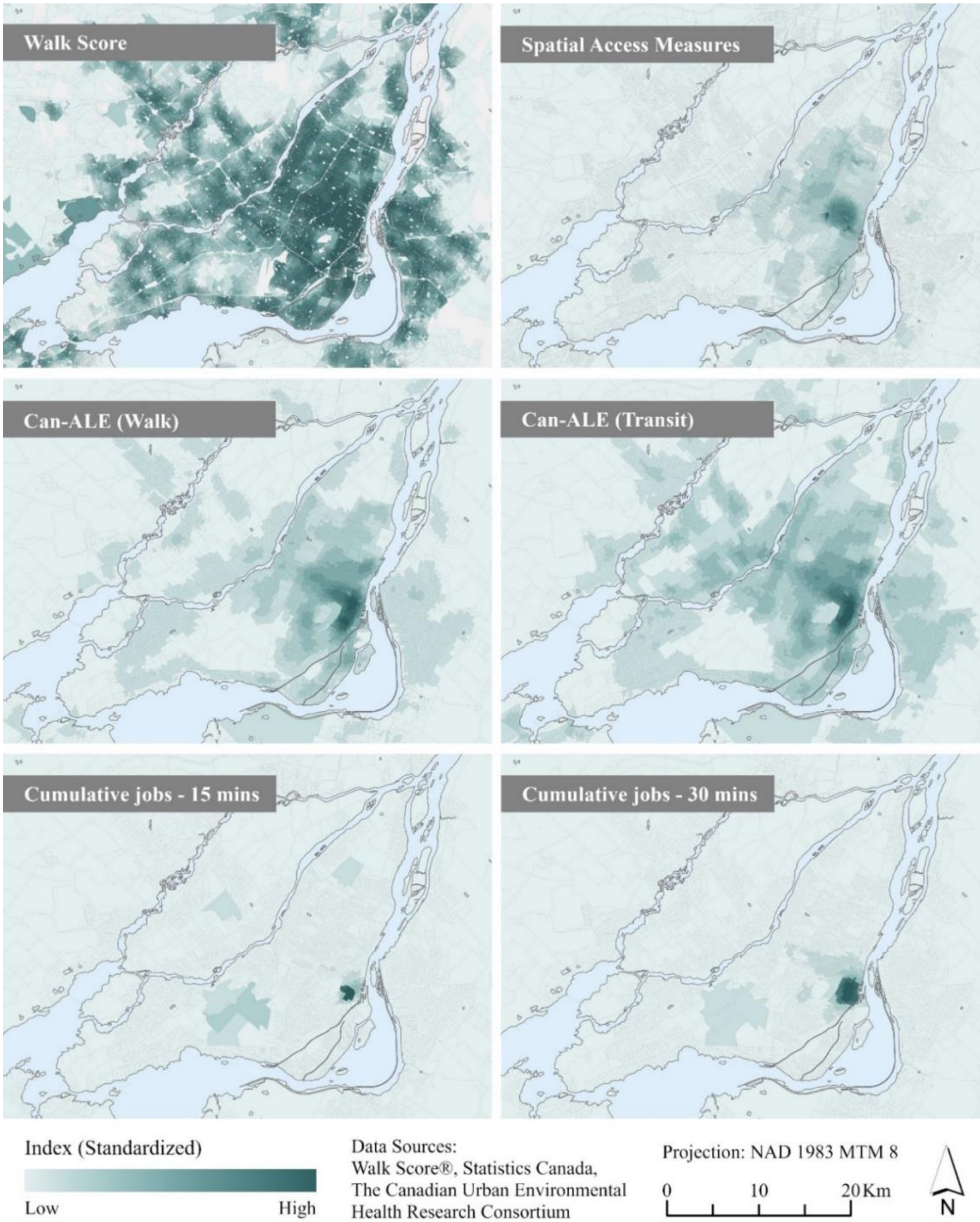

Figure 1. Distribution of the six walkability indices in Montréal

3.3 Methods

The study aims to validate the extent to which different walkability indices predict walking for different purposes. We conduct two main sets of analyses: one that tests the indices for all purposes (work, school, shopping, healthcare, and leisure) combined, and another that tests them for each purpose individually.

For the first set of models (seven models), we predict the percentage of total walking trips for all combined purposes using a multiple weighted linear regression. All models control for the same set of socioeconomic, residential self-selection, and travel identity variables. The first model is a base model where no walkability index was included. Each of the next six models included one of the six walkability indices. The weighting is calculated for all valid responses using the anesrake R package (Pasek, 2018), which follows an iterative raking process (DeBell & Krosnick, 2009). The weights were calculated to match the census-tract information of age, income, and gender obtained from Statistics Canada 2021 census (Statistics Canada, 2023a), which was retrieved through the cancensus R package (von Bergmann et al., 2021). While the results from the weighted regressions were not substantially different than the unweighted ones due to the inferential nature of the analysis, we chose to report the findings from the weighted approach for methodological rigor as it aligns with best practices for complex survey data and accounts for any potential biases in sample representation (Pfeffermann, 1993).

For the second set of models, we follow the same approach as in the first set, yet with the dependent variable being the percentage of walking trips conducted for a specific purpose per week. For each purpose, we use a subset of data that includes only individuals who made at least one trip by any mode to that purpose. We then calculate the percentage of their trips to that purpose done by walking. For example, if an individual made 2 out of 4 shopping trips by walking, their walking mode share for shopping would be 50%. Since seven models were developed for each of the five purposes, this resulted in a total of 35 statistical models. This approach allows for the comparison of the coefficients of determination (R^2) from each model, with the highest R^2 indicating better overall explanatory power, and consequently, better predictability of walking using a particular walkability index.

4 Results

4.1 Descriptive statistics

Table 1 includes descriptive statistics of the data used in the models for the entire sample and categorized by the five examined purposes. Most of the sample was retained for the shopping and leisure analyses, 94% and 82% of the 4,715 participants, respectively. Meanwhile, school trips were performed by the fewest participants in the sample, though still a considerable sample size of 569 participants. The purposes with the highest mean walking mode share were shopping (35.7%) and healthcare (including pharmacies) (42.9%). This can be explained by Montréal's high density of amenities across most areas of the island, as illustrated by the Walk Score data in Figure 1. The city's design, characterized by mixed-use neighborhoods and a concentration of amenities like pharmacies, clinics, and shops within short distances, encourages residents to walk to these destinations. Meanwhile, work has the lowest mean walking mode share of 26.2%. This is likely because individuals tend to travel farther for work, making walking a less viable option (Negm et al., 2023). The mean age is lowest for participants with school trips while the full employment status is at 90% for participants with work trips. Except for Walk Score and Spatial Access measures, the four other walkability indices have higher mean values for school trips, compared to other purposes, which could be explained by students residing near colleges or universities, which tend to be highly walkable areas.

Table 1. Descriptive statistics by mean (standard deviation)

	All purposes N= 4,715		Work N= 2,542		School N= 569		Shop N= 4,429		Leisure N= 3,877		Healthcare N= 3,150	
Dependent variable												
Weekly walking mode share (%)	27.5	(27.3)	12.9	(26.6)	18.2	(30.6)	35.7	(40.6)	22.0	(31.6)	42.9	(46.2)
Socioeconomic, residential self-selection (RSS), and travel identity variables												
Gender [1=Woman]	0.5	(0.5)	0.5	(0.5)	0.6	(0.5)	0.5	(0.5)	0.5	(0.5)	0.5	(0.5)
Age	47.2	(16.6)	43.0	(12.5)	24.6	(7.7)	48.1	(16.2)	47.2	(16.6)	50.2	(16.3)
Income (x 1k CAD)	99.8	(57.3)	111.9	(57)	86.2	(57.2)	99.6	(57.3)	101.1	(57.5)	98.1	(56.5)
Household Size	2.4	(1.2)	2.6	(1.3)	3.1	(1.5)	2.4	(1.2)	2.4	(1.3)	2.4	(1.2)
Employment [1=Full time]	0.6	(0.5)	0.9	(0.33)	0.1	(0.23)	0.6	(0.5)	0.6	(0.5)	0.6	(0.5)
Available Cars	1.1	(0.9)	1.1	(0.9)	1.2	(1.1)	1.1	(0.9)	1.1	(0.9)	1.1	(0.9)
RSS Walkable	0.7	(0.4)	0.8	(0.4)	0.5	(0.5)	0.7	(0.4)	0.8	(0.4)	0.8	(0.4)
Travel Identity [1=Pedestrian]	0.8	(0.4)	0.8	(0.4)	0.9	(0.3)	0.8	(0.4)	0.8	(0.4)	0.8	(0.4)
Walkability indices												
Walk Score*	76.4	(22.5)	76.1	(22.6)	77.1	(22.9)	76.7	(22.4)	76.8	(22.6)	76.6	(22.4)
Spatial Access Measures*	0.2	(0.1)	0.2	(0.1)	0.2	(0.1)	0.2	(0.1)	0.2	(0.1)	0.2	(0.1)
Can-ALE/Transit*	2.9	(3.7)	2.8	(3.6)	3.5	(4.4)	2.9	(3.7)	3.0	(3.7)	2.9	(3.7)
Can-ALE*	3.8	(4.5)	3.7	(4.4)	4.5	(5.3)	3.8	(4.5)	3.9	(4.6)	3.7	(4.5)
Cumulative 15 mins (x 10k jobs) *	0.5	(1.6)	0.5	(1.5)	0.9	(2.7)	0.5	(1.6)	0.5	(1.6)	0.5	(1.5)
Cumulative 30 mins (x 10k jobs) *	2.0	(4.2)	1.8	(3.9)	3.0	(6.13)	2.0	(4.2)	2.1	(4.4)	1.9	(4.0)

*Values were standardized for the regression analysis

4.2 Statistical models

To investigate the relationship between the six walkability indices and travel behavior, we conduct seven multiple linear weighted regressions. The first model is a base model with only the control variables and no walkability index was included. The following six models use the same control variables and a different walkability index in each (Cumulative opportunities with 15- and 30-minutes time thresholds, Walk Score, Spatial Access Measures, Can-ALE, and Can-ALE/Transit). The results of this analysis are displayed in Table 2. Since each index has its own scale—such as 0 to 100 for Walk Score or the sum of three z-scores for Can-ALE—we used standardized values for these indices (z-score) in the regressions. Each index was standardized by subtracting its mean and dividing by its standard deviation, ensuring that all indices were placed on a common scale with a mean of zero and a standard deviation of one, allowing for comparisons between the models.

The base model highlights the importance of individual and household characteristics in explaining travel behavior as they account for 23.4% of the variance in weekly walking mode share. In most subsequent models that include a walkability index, full time employment, higher income, and availability of cars have a statistically significant negative impact on weekly walking mode share, ceteris paribus. Conversely, choosing to reside in a walkable neighborhood and identifying as a pedestrian has a statistically significant positive impact on the percentage of weekly walking trips, while keeping all other variables constant at their mean.

Including the walkability indices in the models offers a better goodness of fit for the six walkability models compared to the base model, with all walkability measures being statistically significant at $p<0.001$. The models incorporating Can-ALE and Can-ALE/Transit had the highest R^2 of 0.317 and 0.314, respectively. Compared to the base model (R^2 =0.234), these two indices show major contribution in explaining walking. The third best performing index was the Spatial Access Measures (R^2 = 0.284), followed by the Walk Score model (R^2 = 0.281). Finally, the cumulative opportunities measures had the weakest prediction power with R^2 of 0.278 and 0.257 for the 30- and 15-minutes time thresholds, respectively.

Table 2. Regression results for the six models with the percentage of total walking trips performed per week as the dependent variable

	Model 0 **Base Model**		**Model 1** **Cumulative jobs 15 mins**		**Model 2** **Cumulative jobs 30 mins**		**Model 3** **Walk Score**		**Model 4** **Spatial access measures**		**Model 5** **Can-ALE transit index**		**Model 6** **Can-ALE walk index**	
	Coef.	95% CI	Coef.	95% CI	Coef.	95% CI	Coef.	95% CI	Coef.	95% CI	Coef.	95% CI	Coef.	95% CI
(Intercept)	**23.64** ***	19.82, 27.47	**20.95** ***	17.15, 24.74	**19.15** ***	15.39, 22.90	**20.44** ***	16.71, 24.16	**21.11** ***	17.40, 24.82	**17.48** ***	13.82, 21.14	**17.31** ***	13.66, 20.96
Gender	-0.07	-1.48, 1.33	0.09	-1.29, 1.47	0.63	-0.74, 1.99	0.16	-1.20, 1.52	0.18	-1.18, 1.54	0.42	-0.91, 1.75	0.49	-0.84, 1.82
Age	0.03	-0.01, 0.08	**0.07** **	0.03, 0.11	**0.09** ***	0.05, 0.14	**0.07** ***	0.03, 0.12	**0.07** ***	0.03, 0.12	**0.13** ***	0.09, 0.17	**0.13** ***	0.09, 0.17
Income [1k CAD]	-0.01	-0.03, 0.00	**-0.02** *	-0.03, -0.00	**-0.02** *	-0.03, -0.00	-0.01	-0.02, 0.00	**-0.02** *	-0.03, -0.00	**-0.01** *	-0.03, -0.00	**-0.02** *	-0.03, -0.00
Household size	**-0.95** **	-1.59, -0.31	-0.57	-1.21, 0.06	-0.38	-1.00, 0.25	-0.48	-1.10, 0.15	**-0.63** *	-1.25, -0.01	-0.19	-0.80, 0.42	-0.14	-0.75, 0.47
Full time empl.	**-6.00** ***	-7.53, -4.46	**-5.29** ***	-6.81, -3.77	**-4.86** ***	-6.36, -3.37	**-5.74** ***	-7.23, -4.25	**-5.73** ***	-7.22, -4.25	**-5.27** ***	-6.73, -3.82	**-5.16** ***	-6.61, -3.71
Available cars	**-8.76** ***	-9.71, -7.82	**-8.22** ***	-9.16, -7.28	**-7.70** ***	-8.63, -6.77	**-6.27** ***	-7.22, -5.31	**-6.53** ***	-7.48, -5.59	**-5.50** ***	-6.44, -4.57	**-5.48** ***	-6.41, -4.55
RSS: Walkable neighborhood	**4.56** ***	2.94, 6.18	**4.09** ***	2.49, 5.68	**3.68** ***	2.11, 5.26	**3.72** ***	2.15, 5.30	**3.21** ***	1.64, 4.78	**2.54** **	0.99, 4.08	**2.37** **	0.83, 3.91
Travel Identity: Pedestrian	**18.79** ***	16.82, 20.75	**18.32** ***	16.38, 20.25	**17.77** ***	15.86, 19.68	**15.91** ***	13.98, 17.84	**16.92** ***	15.01, 18.83	**15.62** ***	13.74, 17.50	**15.69** ***	13.82, 17.56
Standardized Walkability Index ‾			**4.24** ***	3.55, 4.93	**5.91** ***	5.22, 6.59	**6.87** ***	6.10, 7.64	**6.73** ***	6.01, 7.46	**8.87** ***	8.13, 9.61	**8.99** ***	8.25, 9.72
Observations	4715		4715		4715		4715		4715		4715		4715	
R^2 / R^2 adjusted	0.234 / 0.233		0.257 / 0.256		0.278 / 0.276		0.281 / 0.280		0.284 / 0.283		0.314 / 0.313		0.317 / 0.316	

‾ The Walkability index corresponds to the Model name

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

To further investigate the best index for predicting walking for specific purposes, we ran separate models for each of the five purposes where the dependent variable is the walking mode share for each purpose. In the 30 purpose-specific models incorporating a walkability index, the indices were statistically significant at $p<0.001$, except for Walk Score for School trips which was not statistically significant. Table 3 presents the coefficients of determination (R^2) from these 30 regressions, the five base regressions (which do not include a walkability index for each purpose), and the combined purposes' regressions from Table 2.

For strictly utilitarian purposes, such as work and school, the cumulative opportunities measure within 30 minutes outperformed the other five indices. Although this measure showed the best fit for work trips, its R^2 value (0.095) was the lowest compared to the best fits observed for other purposes, such as shopping, which had a best R^2 value of 0.361. This indicates that walkability indices are generally poor predictors for work trips, which aligns with the fact that relatively few work trips are made on foot, as demonstrated in Table 1.

The percentage of walking trips for shopping was best predicted by the Can-ALE/Transit index ($R^2 = 0.361$). The Can-ALE and Walk Score indices provided relatively close fits, with R^2 values of 0.359 and 0.349, respectively. Shopping is the purpose where the increase in model predictability after including the walkability indices is most observed compared to the base model. For leisure, Can-ALE is the best predictor ($R^2 = 0.130$), closely followed by Can-ALE/Transit ($R^2 = 0.127$). Walk Score was only best in predicting healthcare trips ($R^2= 0.246$) with only a slight difference compared to the Can-ALE/Transit index ($R^2 = 0.243$).

Table 3. Coefficient of determinations (R^2) for multiple linear regressions with walking mode share per purpose as the dependent variable

Trip purpose	N	Walkability Index (R2 / R2 adjusted)						
		Base (No Index)	Cumulative jobs 15 mins	Cumulative jobs 30 mins	Walk Score®	Spatial access measures	Can-ALE/ Transit	Can-ALE
Work	2542	0.050 / 0.047	0.074 / 0.071	**0.095 / 0.092**	0.054 / 0.050	0.056 / 0.052	0.067 / 0.063	0.070 / 0.067
School	569	0.061 / 0.047	0.195 / 0.182	**0.215 / 0.202**	0.067 / 0.052	0.083 / 0.068	0.154 / 0.140	0.168 / 0.154
Shopping	4429	0.269 / 0.268	0.279 / 0.277	0.292 / 0.291	0.349 / 0.348	0.334 / 0.332	**0.361 / 0.359**	0.359 / 0.357
Leisure	3877	0.096 / 0.094	0.106 / 0.104	0.124 / 0.122	0.105 / 0.103	0.121 / 0.119	0.127 / 0.125	**0.130 / 0.128**
Healthcare	3150	0.173 / 0.171	0.179 / 0.177	0.190 / 0.188	**0.246 / 0.244**	0.209 / 0.206	0.243 / 0.241	0.238 / 0.236
All purposes	4715	0.234 / 0.233	0.257 / 0.256	0.278 / 0.276	0.281 / 0.280	0.284 / 0.283	0.314 / 0.313	**0.317 / 0.316**

*Each model controls for age, gender, income, household size, full time employment, car availability, residential selection in walkable neighborhoods, and travel identity as pedestrian

** Bolded indicates the highest R^2 for each purpose

5 Discussion

Cities worldwide are developing transport plans that focus on walking and cycling as sustainable modes of transport for a wide number of positive outcomes, including health benefits that come with increased physical activity (Mueller et al., 2015), enhanced well-being (Ferdman, 2019; Singleton, 2019), and the reduction of greenhouse gas emissions (Woodcock et al., 2009). To encourage walking, many cities are adopting the Vision Zero safety strategy that aims to eliminate fatalities or serious injuries involving road traffic (Björnberg et al., 2019; Johansson, 2009; Kim et al., 2017; Ville de Montréal, 2022). Despite the potential exposure to pollution (Ramel-Delobel et al., 2024; Tainio et al., 2021; Vohra et al., 2021), research has shown that pedestrians are less exposed to pollutants than car commuters (Cepeda et al., 2017). Moreover, the health benefits of walking outweigh the risks associated with pollution exposure (Tainio et al., 2016).

Walkability measures are valuable tools that can be operationalized to achieve the walking-related sustainable goals. This research demonstrates that several accessible walkability indices in Canada can reliably estimate utilitarian and discretionary walking behavior. Incorporating these indices into the planning and decision-making processes can support the development of attainable walkability goals. By analyzing their spatial distributions and integrating them with other equity-related aspects such as income levels, areas for potential improvements can be identified. Targeted land use and transport interventions such as increasing building density and providing essential amenities within walking distance can then be implemented to enhance walkability and promote more equitable access to diverse opportunities with active transport modes.

When comparing the predictive power of six walkability indices for walking behavior in Montréal, we found that the Can-ALE and CAN-ALE/Transit indices were the most effective for all purposes in general, as well as shopping and leisure trips in particular. Among the examined indices, these two measures were the only ones that explicitly considered dwelling density, street intersection density, and activity/destination density. Additionally, Can-ALE/Transit included the density of transit stops per DA. Our results show the importance of incorporating these aspects when designing a walkability index that aims to predict walking. As these measures account for the popular 3Ds: density, diversity, and design (Ewing & Cervero, 2010), it is unsurprising that they outperform other measures that ignore some of these components. The Can-ALE and Can-ALE/Transit indices used in this analysis are the sum of z-scores of their components, which can make interpretation and practical application challenging. However, the full dataset provided by the researchers contains detailed values and z-scores for each of the components per DA. The overall index can help highlight areas for potential enhancements, while the detailed component values enable the development of targeted strategies and interventions.

While gravity-based measures such as Spatial Access Measures and Walk Score were shown to be fairly adequate in predicting overall walking mode share, they primarily focus on the availability and density of destinations. This focus makes them less reliable as a comprehensive measure of walkability, an issue that was raised previously regarding Walk Score (Herrmann et al., 2017). It is worth mentioning that the widespread availability and recognition of Walk Score give it a major advantage over the other measures that are specific to Canada. Our results along with previous ones confirm that it is an adequate predictor of non-work walking trips (Hall & Ram, 2018; Manaugh & El-Geneidy, 2011). It is important to note that these measures have separate indices for each destination type, which could be useful for specific interventions targeting walkability for certain purposes. However, interpreting these gravity-based measures is challenging, as it is difficult to understand what an increase of one unit implies. This complexity makes them less practical for policy application compared to more straightforward indices.

Despite cumulative opportunities measures for jobs not being commonly used as walkability indicators, they proved to be better than other indices in estimating the walking mode share for utilitarian purposes, however, with a relatively low R^2. This aligns with their use in the transport literature as indicators for commute mode share (Cui et al., 2020; Negm & El-Geneidy, 2024). One of the reasons that could make these measures less reliable to predict overall walking behavior is the lack of suitable data to calculate them on a fine-grained level. The data available from the Canadian commuting flows and census undergo data suppression when retrieved for smaller geographical units than census tracts, which makes it challenging to correctly estimate the jobs' distribution.

When selecting a walkability measure for practical use, the accessibility and interpretability of an index are crucial for its adoption. A publicly available index allows for a wide range of stakeholders to incorporate it in their decision-making process, while an easily interpretable index allows for effective communication to the public and policymakers. If an index is too complex or difficult to breakdown, it could be overlooked. Designing context-specific walkability indices should prioritize these considerations. Additionally, the availability of data and the technical requirements for calculating the indices are crucial for their potential replication and implementation across different regions. Ensuring the validity of walkability indices by comparing them to actual walking behavior and perceptions is essential for their reliability and effectiveness in guiding policy and urban planning decisions.

6 Conclusion

Developing walking indices that are easily accessible and interpretable is essential in encouraging their adoption in practice. In this research, we compare the ability of several walkability indices to predict walking behavior. Along with Walk Score, a freely available walkability index for many regions, we compare walkability indices that were specifically developed for Canada: The Canadian Active Living Environments (Can-ALE) index and its extended version Can-ALE/Transit, Spatial Access Measures, and cumulative opportunities measures. We use data from the Montréal Mobility Survey with a sample of 4,715 participants to perform multiple linear weighted regressions to estimate the impact of six walkability indices on weekly walking mode share for five purposes: work, school, shopping, leisure, and healthcare. We then use a subsample of the participants to examine the impact of these indices on weekly mode share for each trip purpose separately. We find that Can-ALE and CAN-ALE/Transit had the strongest predictive power for the percentage of walking trips performed per week for all purposes in general, as well as shopping and leisure trips in particular. This is likely due to these two measures being the only ones that directly account for dwelling, street intersection, and destination density, making them comprehensive measures of walkability.

While our study focuses on Montréal due to the availability of survey data, these walkability indices are available across Canada and could be examined in different cities with various urban densities to explore their effectiveness in rural, suburban, and urban settings. The investigated walkability indices are designed at the macro-scale, future research can investigate more detailed walkability indices, such as the ones that account for micro-level features (Ki et al., 2023) or thermal comfort (Labdaoui et al., 2021). These indices can be validated through street audits to assess their reliability in capturing key features that contribute to high-quality pedestrian environments (Clifton et al., 2007; Millstein et al., 2013). This study is limited by the availability of survey data and walkability indices data from specific years and spatial levels. Other data sources, such as GPS and Mobile data apps that track walking and physical activity (Rundle et al., 2016), or pedestrian counts using manual or automated methods (Cambra & Moura, 2020) can be used to validate walkability indices in future studies. It is important to note that updated versions of the walkability indices used in our analysis, with consistent calculations and release dates, may produce different results in subsequent studies. This research used recent and widely available walkability indices in Canada, future research can expand the comparisons to other measures that require calculations, similar to previous research (Lefebvre-Ropars & Morency, 2018; Manaugh & El-Geneidy, 2011). Whilst the findings are specific to the Canadian context due to data availability, future research can apply these measures to other regions, as the used indices such as Can-ALE have detailed and open access documentations (Ross et al., 2018).

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Author contribution

Conceptualization, data curation, formal analysis, investigation, methodology, project administration, validation, visualization, writing–original draft, writing–review & editing: Hisham Negm; conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing–original draft, writing–review & editing: Ahmed El-Geneidy.

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