Association between accessibility to key activities through multi-modal public transit network in the Montréal Metropolitan Region and subjective well-being

Chérine Zaïm

Department of Epidemiology, Biostatistics and Occupational Health

McGill University

Montréal, Québec

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Abstract

Background: Access to physical locations and social networks determines how we create relationships with each other and how we can access material goods or intangible resources like knowledge and activities through which we can better our lives. Public transit may in that context influence individual subjective well-being through both the transit experience (during the trip) and as a mean of accessing key locations to meet our basic needs and promote personal development, increasing one's satisfaction with their life.

Goal: Using data from the 1st wave of Montréal participants from INTERACT, collected in 2018, this cross-sectional cohort design aims to determine if public transit accessibility is associated with increased subjective wellbeing scores at the individual level.

Methods: 833 participants completed the VERITAS questionnaire (map-based survey) for the first cycle of the INTERACT study in 2018. The main exposure, the fit between transportation needs and public transit offer at the individual level (transit fit measure), was a new metric developed using open-access data from Google Maps. The outcome of interest, life satisfaction (a component of subjective well-being), was measured using the Personal Well-being Index 5th Edition (PWBI score). Multiple linear regressions were performed to characterize the association between the main exposure and subjective well-being, controlling for the frequency of public transit use and other covariates that could have an influence on public transit use and well-being (car ownership, age, gender, education level and physical health).

Results: A multiple linear regression model adjusting for yearly transit use, car ownership, age, gender, education, and physical health showed an average increase of 0.99 points in the PWBI score per increment of 1 in the transit fit measure (β *= 0.99 with 95% CI [-0.40, 2.38]*), which was not statistically significant. Age (β *= 0.15 with 95% CI [0.08, 0.22]*), reported physical health (β *= 0.50 with 95% CI [0.37, 0.63]*) and education level points (β *= 3.97 with 95% CI [1.37, 5.58]*) were associated with life satisfaction. There is a strong signal that high public transit use ≥ 5 times/week) is negatively associated with life satisfaction (β *= -3.46 with 95% CI [-7.19, 0.27]).* The model using all covariates had an adjusted R^2 of 0.1075, meaning that this model only explained 10.75% of the variance of the outcome variable.

Conclusions: A novel public transit accessibility measurement methodology was developed based on fit between a user's lifestyle choices (through daily-activities-related trips) and public transit offer, which will need further refinement. Further research should be done to enhance our understanding of the mechanisms underlying the complex relationship between access to public transport and subjective well-being. Public transit can have an impact on individuals' subjective well-being through multiple pathways, which highlights the need for an integrated, intersectoral strategy to increase access.

Résumé

Contexte : L'accès aux lieux physiques et aux réseaux de contacts sociaux détermine comment nous créons des relations avec les autres et comment nous pouvons accéder aux biens matériels ou aux ressources immatérielles, comme des connaissances et des activités grâce auxquelles nous pouvons améliorer notre vie. Le transport en commun peut dans ce contexte influencer le bien-être subjectif individuel à la fois par l'expérience du transport (pendant le voyage) et comme moyen d'accéder à des endroits clés pour répondre à des besoins fondamentaux et promouvoir le développement personnel, augmentant ainsi la satisfaction de chacun à l'égard de sa vie.

Objectif : À l'aide des données de la 1ère vague de participants montréalais d'INTERACT, recueillies en 2018, cette étude transversale vise à déterminer si l'accessibilité au transport en commun est associée à des scores de bien-être subjectif plus élevés au niveau individuel.

Méthodes : 833 participants ont rempli le questionnaire VERITAS (enquête cartographique) pour la 1ère vague de l'étude INTERACT en 2018. L'exposition principale, l'adéquation entre les besoins de transport et l'offre de transport en commun au niveau individuel (mesure d'adéquation ou « transit fit measure »), était une nouvelle mesure développée à l'aide de données en libre accès de Google Maps. La variable d'intérêt, la satisfaction à l'égard de la vie (une composante du bien-être subjectif), a été mesurée à l'aide de l'indice de bien-être personnel 5e édition (score PWBI). Des régressions linéaires multiples ont été effectuées pour caractériser l'association entre l'exposition principale et le bien-être subjectif, en contrôlant pour la fréquence d'utilisation des transports en commun et d'autres variables (possession d'une voiture, âge, sexe, niveau d'éducation et santé physique).

Résultats : Un modèle de régression linéaire multiple ajusté pour la fréquence annuelle d'utilisation des transports en commun, la possession d'une voiture, l'âge, le sexe, le niveau d'éducation et la santé physique a montré une augmentation moyenne de 0,99 point du score PWBI par incrément de 1 dans la mesure d'adéquation (β = 0,99 avec 95 % IC [-0,40 ; 2,38]), ce

qui n'était pas statistiquement significatif. L'âge (β = 0,15 avec IC à 95 % [0,08 ; 0,22]), l'état de santé physique déclaré (β = 0,50 avec IC à 95 % [0,37 ; 0,63]) et le niveau d'éducation (β = 3,97 avec IC à 95 % [1,37 ; 5,58]) ont eu un effet statistiquement significatif sur la satisfaction à l'égard de la vie. Il existe une association négative non-significative entre la fréquence d'utilisation élevée des transports en commun ≥ 5 fois/semaine et la satisfaction à l'égard de la vie (β = -3,46 avec IC à 95 % [-7,19 ; 0,27]). Toutes les autres covariables n'étaient pas statistiquement significatives à un seuil de signification de 95 %. Le modèle utilisant l'ensemble des covariables avait un R^2 ajusté de 0,1075, ce qui signifie que ce modèle n'expliquait que 10,75 % de la variance de la variable d'intérêt.

Conclusions : Une nouvelle méthode de mesure d'accessibilité des transports en commun a été élaborée en fonction de l'adéquation entre les choix de mode de vie d'un utilisateur (par le biais des déplacements liés aux activités quotidiennes) et l'offre de transport en commun, qui devra être raffinée davantage. Des recherches supplémentaires devraient être menées pour améliorer notre compréhension des mécanismes sous-jacents à la relation complexe entre l'accès aux transports en commun et le bien-être subjectif. Le transport en commun peut avoir un impact sur le bien-être subjectif des individus de multiples façons, ce qui souligne la nécessité d'une stratégie intégrée et intersectorielle pour en augmenter l'accès.

Preface

This thesis consists of six chapters, as follows:

- An introduction (**Chapter 1**), which lays out the objectives of the current thesis, as well as provides a description of the INTERACT study from which the data was sourced, the political and social context in which the study was developed, and a brief overview of the intersection of public transportation and well-being (as well as definitions for the main concepts touched upon in this thesis);
- A literature review (**Chapter 2**), where the main landmark studies on the association between public transit and wellbeing will be discussed, as well as literature on possible factors that could influence this relationship;
- A Methods chapter (**Chapter 3**), where the methods used for this study will be explained, including the definition of variables used and the approach used to calculate each participant's walking distance to transit stops using Geographic Information Systems (GIS) methods. The development of statistical models to answer the thesis' hypothesis will also be discussed;
- Note that an entire substantive chapter (**Chapter 4**) will be dedicated to the development of the travel time ratio measure, including an overview of the current literature on public transit accessibility metrics, reasons underlying the development of this new measure, descriptive statistics as well as a face-value validation of this new metric compared to other established accessibility measures;
- A Results chapter (**Chapter 5**), which reports the descriptive statistics pertaining to public transit use and covariates measured in the sample. Statistical models' results are also reported for the association between the travel time ratio and wellbeing scores, accounting for covariates described in the Methods chapter; and
- A Discussion chapter (**Chapter 6**), the final chapter, in which the limitations of the study are discussed, as well as substantive knowledge contributions of the thesis and possible future research avenues to explore.

Ethics Statement

This thesis was funded by McGill University through the Public Health and Preventive Medicine residency program and through the salary provided to me by the Régie de l'assurance maladie du Québec.

The research data used in this project was provided by the INTERACT team (INTERACT: INTErventions, Research, and Action in Cities Team) was received from Canadian Institutes of Health Research (*Funding Reference Number*: IP2-1507071C), under the grant competition for Environments and Health: Intersectoral Prevention Research on July 13th, 2016 (*Competition Code*: 201607IP5Team). INTERACT was approved under the name "INTERACT: INTERventions urbaines, Recherche-Action, Communautés et sanTé" (*Study Reference Number*: CÉR CHUM 16.397) by the Comité éthique de la recherche – Centre hospitalier de l'Université de Montréal (CÉR CHUM).

This specific M.Sc. project was approved by INTERACT as per procedure. It also received approval by the McGill Faculty of Medicine and Health Sciences' Institutional Review Board (*IRB Internal Study Number*: A03-E12-22A). All data used for analyses was stored and manipulated using an encrypted virtual container (VeraCrypt). All guidelines indicated in INTERACT's Data User guidelines for data management were followed. Data was anonymized when necessary.

Contribution of Authors

The thesis committee consisted of 2 co-supervisors (Nancy Ross and Yan Kestens), as well as a Public Health and Preventive Medicine physician affiliated with the Department of Epidemiology, Biostatistics and Occupational Medicine (Sidonie Pénicaud).

Chérine Zaïm

- Performed geo-spatial analyses on data provided by INTERACT;
- Created outcome and exposure variables;
- Performed the statistical analysis as necessary;
- Interpreted the results; and
- Wrote the thesis.

Nancy A. Ross, Ph.D.

Professor in the Department of Geography and an Associate member in the Department of Epidemiology at McGill University

- Co-supervised the thesis; and
- Oversaw all aspects of the thesis, including the development of the methods, the interpretation of the results and the editing of the final thesis.

Yan Kestens, Ph.D.

Professor in the Department of Social and Preventive Medicine at École de santé publique de l'Université de Montréal, and principal investigator of the INTERACT project

- Provided data;

- Co-supervised the thesis; and
- Oversaw all aspects of the thesis, including the development of the methods, the interpretation of the results and the editing of the final thesis.

Sidonie Pénicaud, M.D., M.Sc.

Assistant Professor in the Department of Epidemiology, Biostatistics and Occupational Medicine, and Public Health physician at Direction régionale de santé publique de Montréal

- Member of the thesis committee; and
- Involved in the development of the methods, conceptual frameworks, and the editing of the final thesis.

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List of Acronyms

API: Application Programming Interface

ARTM: Metropolitan Regional Transportation Authority (*Autorité régionale de transport métropolitain*)

CMM: Montréal Metropolitan Community (*Communauté métropolitaine de Montréal*)

EMA: Ecological Momentary Assessments

GIS: Geographic Information System

GPS: Global Positioning System

GTFS: General Transit Feed Specification

HTTPS: Hypertext Transfer Protocol Secure

INTERACT: INTErventions, Research, and Action in Cities Team

LS: Life Satisfaction

O-D: Origin-destination

OECD: Organisation for Economic Co-operation and Development

PCS-12: Physical component summary score

PWBI: Personal Well-Being Index

RTL: *Réseau de transport de Longueuil*

SF-12: 12-Item Short Form Health Survey

SF-36: Medical Outcomes Study 36-Item Short-Form Health Survey

STL: *Société de transport de Laval*

STM: *Société de transport de Montréal*

SWB: Subjective well-being

VERITAS: Visualisation, Evaluation and Recording of Itineraries and Activity Spaces

Chapter 1: Introduction

This chapter will provide an explanation of this thesis' main goal and specific objectives, as well as provide basic definitions for main concepts central to this study. The underlying rationale for the study will also be explained to motivate the choice for the current thesis' topic.

The current study is embedded in the INTErventions, Research, and Action in Cities Team (INTERACT) research program, a pan-Canadian collaboration network measuring the impact of urban form interventions on a multitude of health-related outcomes in four Canadian cities: Montréal, Vancouver, Victoria, and Saskatoon (Team INTERACT, 2020). The INTERACT project aims to evaluate the impact that the Montréal Community 2016-2020 sustainable development plan has had on the health of its citizens (Montréal, 2021).

Objectives

The overarching goal of this thesis is to better understand the relationship between public transit accessibility to key individual destinations and well-being. Using data from the 1st cohort of Montréal participants from INTERACT, collected in 2018, this cross-sectional design aims to determine if public transit accessibility is associated with increased well-being scores at the individual level. The specific objectives of this thesis are:

- To develop a simple indicator to compare accessibility to key locations (specific spatial anchor points) by public transit versus by car at the individual participant level. In other words, this indicator is a travel time ratio (*referred to as the transit fit measure from now on*), using open-access data;
- To describe public transit accessibility using the transit fit measure in the Montréal Metropolitan Region and compare it to other described metrics in the literature for face-value validation; and

- To characterize the association between accessibility to public transit and one aspect of subjective well-being, life satisfaction, controlling for the frequency of public transit use and other covariates.

Our hypothesis is that, at the individual level, increased public transit accessibility would be associated with increased life satisfaction scores, even when accounting for car ownership and individual factors that may affect public transit use.

Definitions

The exposure variable in this thesis encompasses two concepts that may be useful to define as they will be used multiple times in the coming chapters.

Public transit (also referred to as public transportation, mass transit, or transit) can be defined as "a variety of transit options such as buses, light rail, and subways [...] [which] are available to the general public, may require a fare, and run at scheduled times" (Robert Wood Johnson Foundation, 2017). In the context of this study, public transit includes:

- the subway and bus system operated by the *Société de transport de Montréal* (STM);
- the bus systems operated by the *Société de transport de Laval* (STL) and the *Réseau de transport de Longueuil* (RTL); and
- the suburban rail network operated by EXO.

It does not include formal carpooling systems, taxi buses, taxis, other rideshare services or specialized public transit options.

Accessibility refers here to the "ease of reaching valued destinations" via different modes (El-Geneidy & Levinson, 2006). This concept will be developed further in the thesis as it is the theoretical basis for the development of the transit fit measure.

The outcome of interest here is **well-being**, which can be defined as “the presence of positive emotions and moods (e.g., contentment, happiness), the absence of negative emotions (e.g., depression, anxiety), satisfaction with life, fulfillment, and positive functioning” (Centers for Disease Control and Prevention, 2018). Individual well-being is a complex concept to define and thus, many definitions have been proposed and will be further discussed in this thesis’ literature review. This study will focus on life satisfaction, which is a subset of subjective well-being.

Rationale

Mobility in the context of this study is defined as “the intention and realization of an act of movement in physical space that involves social [objectives]” (Kaufmann, 2015). As a broader sociological construct, this concept is used as a lens through which human activity is analysed based on physical movements that are impacted by social constructs, which determine how we gather food, how we create relationships with each other and how we can access material goods or intangible resources, like knowledge and activities, through which we can better our lives. This is at the heart of the human experience. As explained by Kauffman, urban societies can be analysed through a mobility lens via three dimensions:

- the *field of possibilities* (potential mobility experiences as influenced by the development, configuration, and performance of physical transportation networks and social constraints like institutions and laws, or the job market);
- the *aptitude for movement* or *motility* (one’s potential for movement through accessibility, mediated by individual factors like time constraints, technological tools or means of transportation, skills, and ability to appropriate those to move through space and social context); and
- actual *movement* in space (Kaufmann, 2015).

The aim is then to access something through this process, whether it is a necessity in the form of a material good or an intangible social need such as higher social status. In that context, access to people, places, activities, resources, goods, and information is indeed essential for most activities. One requirement for access is physical proximity or, alternatively, possessing the means to bridge the space constraints to access those resources at a reasonable cost (be it time, distance, monetary or psychological effort) for the individual (Lynch, 1981). Public transit is one of those means to overcome spatial constraints to access resources.

Several studies have highlighted that travel affects well-being and self-realization potential through multiple mechanisms, whether it is through the ability to participate in outside activities, fulfillment during the act of travel or mobility opportunities (De Vos et al., 2013; Delbosc, 2012; Jakobsson Bergstad, et al., 2012). Optimized mobility may allow for more social interaction, which also seems to be a driver of increased well-being and vice versa (Diener & Seligman, 2002; Lansford, 2000). Diener et al. (2010) argues that individuals with positive affect may also develop stronger social relationships, which promote increased well-being through positive feedback loops.

Equity concerns arise when individuals who may not have physical proximity to needed resources also lack adequate transportation options to access these opportunities (be it because of lack of income, disability, or lack of cognitive or technical skills). The concept of captive ridership, i.e., people "who do not have immediate access to private transportation or who otherwise must use public transportation in order to travel" (The National Academies of Sciences, Engineering and Medicine, 2021) reflects this conundrum that so many of us face to access everyday resources. For older individuals or people living with disabilities, for whom public transit may be a support to maintain autonomy in their daily activities, challenges around accessibility are at the forefront of the mobility experience and potential for access to essential resources, especially for low-income and non-white subgroups (Dale Nordbakke, 2019; Hess, 2009; Blais, 2013). As universal access is unequally implemented within most Canadian public transit systems with abounding physical barriers that may hinder access for people living with disabilities, the impact of lack of transportation on employment opportunities can lead to disproportionate prejudice for people who may already be at a disadvantage in the workplace (Grisé et al., 2018; Lillie et al., 2013).

Moreover, barriers to public transit include not only physical accessibility and ease of use, but also monetary accessibility in the form of transit affordability (Sengupta et al., 2013). Particularly in low-income individuals, the lack of access to reliable transportation – a car in this specific study by Morris et al (2020) – can be detrimental to the realization of out-of-home activities, including employment. Limited access to public transit has been found to be a major barrier to accessing recreational activities for children and youth in Canada (Hanvey, 2001; Sengupta et al., 2013). However, public transit, when coupled with policies that aim to tackle affordability, can help reduce transportation costs for these groups thus freeing up money to be spent on other necessities.

Perception of transit is integral to the transit experience and may contribute to subjective well-being, especially in the context of captive ridership that may not have chosen to use public transit as a primary transportation mode (Ettema, et al., 2011; van Lierop & El-Geneidy, 2017). Perceived quality and efficiency of public transit are two of these components, the assessment which can be expressed through quality-of-service parameters both quantitative (e.g., walking distance, travel time, number of transfers, waiting time, crowding, etc.) and qualitative (user's perception of the quality of service, safety, cleanliness of stations, etc.) (Kittelson & Associates et al., 2003). An especially crucial influence on users' satisfaction, service frequency seems to be one of the keys to retaining their loyalty to a public transit system. In the same vein, transit reliability is one of the most important factors that influence ridership retention through increased user satisfaction (Perk et al., 2008).

Perception of public transit also modulates how we experience our journey itself. Trip satisfaction can be affected by general pleasantness of the experience and purpose of the trip, as well as the modes used. Contradictory data is available regarding the impact of public transit on mood, which is “the way you feel at a particular time” (Cambridge Dictionary, 2021). A study by Morris and Guerra (2015) showed that, although travel doesn’t seem to significantly alter mood, bus and train users seem to experience more negative emotions during transit than those using cars (passengers or drivers) or bicycles, which seem to be corroborated by other studies (Ye & Titheridge, 2014; Künn-Nelen, 2016). Similarly, a Canadian study looking at 33 urban regions presented similar outcomes, with public transit (all modalities) in general being the most stressful mode of transportation (Haider et al., 2013). One of the reasons may be that crowdedness and proximity to other passengers have been shown to lead to adverse emotions in North American train passengers (Evans & Wener, 2007). However, car drivers from the Metropolitan New York City report more negative emotions and stress associated with their commute than transit users, with effort exerted and predictability of the commute having mediating effects on the stress and mood reported (Wener & Evans, 2011). These two seemingly incompatible findings could be reconciled by examining the contexts within which this data was collected. Transit systems in areas that are developed to cater to cars may be inherently less predictable or require more effort to navigate (whether through multiple transfers or complex transit routes) than the equivalent commute by car, whereas the opposite could be true for those areas where public transit is prioritized in transportation policy, such as in the Metropolitan New York City. Those systemic characteristics can in turn affect trip satisfaction and mitigate the perception of crowdedness in high-density transit environments and its effects on commuter stress (Lunke Bjørnson, 2020; Cox et al., 2006).

Safety, waiting times, and need for transfers (which, as previously mentioned, are quality-of-service indicators) can affect perception of public transit. Multiple authors pose the hypothesis that transit stops, especially those within public spaces, can become crime generators i.e., “spaces offenders are attracted to, but do not have inherent criminogenic characteristics”. Furthermore, transit stops near crime-prone environments (e.g., bars, vacant buildings, generally unkept, or derelict areas with graffiti or litter) may serve as crime attractors (Savard, 2018; Brantingham & Brantingham, 1995; Loukaitou-Sideris et al., 2001). Otherwise crime-neutral environmental nuisances around transit stops, such as increased foot traffic and noise, can also affect well-being and trip satisfaction through safety perception for some populations such as women and seniors. Previous direct or indirect experiences of crime seem to be a strong predictor of safety perception (Abenoza et al., 2018; Yavuz & Welch, 2010; Loukaitou-Sideris, 2014). Women have been shown to be more likely to be victims of crime in certain public settings, including transit environments (Savard, 2018). This relates to the larger context of fear of public spaces, highly influenced by gender and age, which may result to compensating behaviors to anxiogenic transit environments, as well as reduced enjoyment and use of public amenities including public transit due to fear of crime (Chowdhury & van Wee, 2020; Loukaitou-Sideris, 2011; Koskela & Pain, 2000; Ceccato, 2016).

Current evidence linking public transit and subjective well-being is inconsistent – even more so in the case of data on the specific association between public transit accessibility and well-being (Chatterjee, et al., 2020). In addition to its mood-related effects during the trip, public transit can also have direct or indirect effects on the long-term health of its users – and as numerous studies have shown, psychological and physical health are significant predictors of subjective well-being (Cross et al., 2018; Lombardo et al., 2018; Diener et al., 2017; Kayonda et al, 2017). Beyond known population-level benefits of increased public transit use, such as pollution reduction and decreased traffic-related injuries, it can also have direct and indirect positive health effects on individuals (Litman, 2020). For example, increased public transit use in workers has also been associated with lower prevalence of major depressive disorder, suicidal thoughts, or other diagnosed mental illnesses in that population at the sub-state level in the United States (Ferenchak & Katirai, 2015). Similarly, lack of or limited access to public transit can also be detrimental to one's overall health beyond hindering employment and out-of-home potential as discussed previously, including by acting as a barrier of access to health services, preventative care, and condition-specific resources, as well as access to healthy foods (Sengupta et al., 2013). Multiple studies show that longer commutes regardless of mode are associated with multiple physical ailments such as increased blood pressure, anxiety, and musculoskeletal disorders (Koslowsky et al., 1995).

This section served as an overview of the theoretical bases of this thesis' hypothesis, namely that increased public transit accessibility may be associated with increased subjective well-being scores. The idea that mobility through public transit acts as a physical means to access paths to individuals' wellness-promoting resources and, conversely, that public transit – through environmental and individual factors – may negatively affect well-being were discussed briefly. The next chapter, Chapter 2 (Literature Review), will go further into details about the main themes of the thesis, well-being, and accessibility, as well as lay out the current portrait of public transit use within the Montréal Metropolitan Community (CMM; *Communauté métropolitaine de Montréal*).

Chapter 2: Literature Review

This chapter serves as an overview of the theoretical concepts used in this study. In the first part, different theories of subjective wellbeing will be discussed, including different factors that can influence well-being in this study. Thereafter, specific recent studies on the association between subjective well-being and public transit accessibility will be discussed to describe the knowledge basis for this study. Finally, current knowledge gaps in the literature will be discussed to understand how the current study contributes to the field.

Theoretical foundations of subjective well-being

As discussed briefly in the Introduction chapter (Chapter 1), well-being is a complex and often ambiguous concept in health and psychology research, that can be measured both on a societal or individual level. Well-being can be essentially divided in two broad domains: objective and subjective well-being.

Objective well-being explores "objective dimensions of a good life", which was traditionally claimed to be measured by a country's gross domestic product (GDP) as a proxy of standard of living indicators on a societal level (Osbert & Sharpe, 2001). However, the over-reliance on GDP was criticized as reductionist. To move beyond the GDP as a sole indicator of a country's well-being, efforts were made to develop new indicators of objective well-being, culminating in the recommendations outlined in the 2009 report of the Commission on the Measurement of Economic Performance and Social Progress piloted by Stiglitz and Fitoussi. This work was followed by the High-Level Group on the Measurement of Economic Performance and Social Progress in 2013, sponsored by the Organisation for Economic Co-operation and Development or OECD (OECD, 2020). Multiple organizations and research groups have developed conceptual frameworks of varying complexity to describe objective well-being and domains that constitute it. As an example, drawing from the OECD and United Nations Development Fund frameworks, Voukelatou et al. (2020) identified six such domains for their measurement of objective well-being: health, job opportunities, socioeconomic development, environment, safety, and politics.

It is also in this context of increased emphasis on a more holistic view of well-being measurement that more attention was given to the development and use of indicators of subjective well-being, which capture information that is otherwise not measured by defined objective indicators (Stone & Krueger, 2018). **Subjective well-being** (also referred as perceived well-being or happiness) is a psychological construct “characterized by the individual’s internal subjective assessment, based on cognitive judgments and affective reactions, of their own life as a whole” (Lee Kum Sheung Center for Health and Happiness, 2017), although it is influenced by conditions that can be measured objectively, such as poverty, disease, and unemployment. Researchers and policymakers alike can harness this data to analyse the more “intangible” experience of peoples’ lives and understand how life satisfaction is interconnected with the political, economic, socio-cultural, and physical environments within which a society or individual evolves. While researchers do agree that individual characteristics, personality traits, culture, values, and attitudes influence one’s perceived life satisfaction (Argyle, et al., 1999; Diener et al., 2003; Weiss et al., 2008; Ryan & Deci, 2001), available evidence has shown that individual subjective well-being measures are strongly associated with major social determinants of health. This underlines the importance of integrating those measures into both research and policymaking focused on improving social determinants of health to understand how specific policies may affect subjective well-being and help prioritize strategies to tackle societal problems (Steptoe et al., 2015; Kahneman & Deaton, 2010). Enhanced subjective well-being not only makes people feel better about their circumstances, but it is also associated to increased creative thinking, positive social qualities that ultimately lead to greater success, increased earning power as well as better physical health and survival (Diener, et al., 2017).

For the remainder of this chapter, we will focus on the conceptual basis of individual subjective well-being (SWB), our outcome of interest.

Concepts of hedonic and eudemonic well-being

In the field of positive psychology, some researchers hypothesise that individual SWB, the main outcome of the current study, can be divided into two conceptual constructs, hedonic and eudemonic well-being, based on the philosophical Aristotelian origins of those concepts. **Hedonic well-being** (also referred as experienced or emotional well-being) is characterized as the "frequency and intensity of emotional experiences such as happiness, joy, stress, and worry that make a person's life pleasant or unpleasant" (Kahneman & Deaton, 2010). On the other hand, **eudemonic well-being** (sometimes referred as psychological well-being) is understood to be related to "people's perceptions of the meaningfulness (or pointlessness), sense of purpose, and value of their life" (Stone & Mackie, 2013). However, this simplistic divide is more and more contested: some argue that both conceptions overlap in practice (Henderson et al., 2013), or are at the very least strongly correlated (Waterman, 1993; Compton, et al., 1996; Maddux, 2018). SWB assessment traditionally consists of three different components: life satisfaction, the presence of positive mood, and the absence of negative mood – unifying both hedonic and eudemonic prerogatives (Maddux, 2018; Busseri & Sadava, 2011; Veenhoven, 2009). Although most theorists agree that both hedonic and eudemonic well-being are necessary to promote and maximise psychological wellness, much debate exists around the assessment of SWB and its accuracy to measure well-being at all – with some psychologists rejecting either the hedonist or eudemonic paradigms and invalidating SWB as a measure of well-being. Despite the different viewpoints about the definition of well-being, the middle position, that is to accept SWB as a valid measure of well-being regardless of which paradigm is preferred or "correct" for the authors, has been the driver of the last decade in well-being research (Ryan & Deci, 2001).

Data sources and measures of subjective well-being

A typology of data sources used in SWB assessment has been proposed recently by Voukelatou et al. (2021). As expected, as SWB involves subjective experiences – affective or cognitive – most measurement methods revolve around self-reported data or, in the case of novel data collection methods using Big Data, content that is produced by individuals.

SWB is traditionally measured with surveys collecting self-reported data. This approach has been validated thoroughly using a variety of different tools for a multitude of specific well-being domains, and therefore has the advantage of also providing accurate and temporally stable measures of SWB that can often be compared across cultures and specific patient populations. However, such surveys do not accurately measure participants' current mood and temporal variation may not be reflected in the collected data. Ecological Momentary Assessments (EMA) can help address this pitfall of surveys by enabling regular momentary measurement of affect during activities, reducing the potential for recall bias, and making possible the analysis of temporal trends in the data collected. Another validated method developed by Kahneman et al., the Day Reconstruction Method, consists of journaling activities (including their duration) and affective experiences of the previous day to provide data that is more complete and richer than global retrospective assessments done via surveys (Kahneman, et al., 2004). Novel data sources, like sentiment analysis of social media posts, Google Trends, crowdsourced reports, and news report analysis, are increasingly used to assess SWB on a population scale, although it may be difficult to address individual SWB measurement with these methods.

We will focus on survey data for the remainder of this chapter as it represents the bulk of well-being data collected for the purpose of this study; EMA data was also collected but will not be used in this specific study (Kestens, et al., 2019). There exist multiple validated scales that can be used to measure well-being, each tailored for specific needs and contexts. This was recognized by VanderWeele et al. (2020) who, following an interdisciplinary workshop with well-being experts in April 2018, presented recommendations on well-being measures to be used depending on contexts and aims of the study being undertaken.

Life satisfaction as a component of subjective well-being

As discussed earlier, life satisfaction (LS) is one of the main components of SWB according to the seminal paper published by Diener in 1984 – the cognitive or evaluative dimension of SWB, as opposed to the affective dimensions that are represented by positive or negative affect. In 1996, Cummins further added to those original dimension seven specific LS domains derived from the Comprehensive Quality of Life Scale headings: material well-being, health, productivity, intimacy, safety, community, and emotional well-being (Cummins, 1996). However, this method was deemed to be psychometrically invalid (Cummins, 2002) leading the way for the development of the Personal Well-Being Index (PWBI). The PWBI was one of the measurement tools chosen by the INTERACT research group to capture SWB. More specifically, this self-completed scale aims to answer the question: "How satisfied are you with your life as a whole?" by assessing different domains of life satisfaction (LS) (International Wellbeing Group, 2013). It will be discussed in more details in the Methods section (Chapter 3).

Social determinants of health and life satisfaction

LS, and SWB in general, are affected by a multitude of factors, both internal (like personality traits and genetic predisposition to certain affective experiences) and external (like income, educational attainment, etc.) to the individual. Many theorists argue that external factors play only a small role in individuals' well-being – as low as a 10% contribution according to Lyubomirsky et al. – and that happiness may be defined by a set point that is genetically determined and stable through time and life circumstances, although not all experts agree on that statement (Brown & Rohrer, 2020; Lyubomirsky, Sheldon, & Schkade, 2005; Lucas, 2007; Diener & Seligman, 2002; Diener, 1984). This leads us to acknowledge that there may be two types of relationships that exist when looking at how overall LS affects specific domain satisfaction (Schimmack, 2008; Rojas, 2006; Headey et al., 1991; Diener, 1984). A bottom-up approach occurs when individuals develop a sense of overall LS *because* they are at some level satisfied with specific domains in their lives. A top-down approach, on the other hand, occurs when LS predates domain-specific satisfaction and affects – positively or negatively – the individual's appreciation of their satisfaction with specific life domains, due to internal factors such as genetics or personality traits developed through life experience. Both approaches have been used in the literature to explain the causality of LS.

The bottom-up pathway is particularly interesting in the context of this thesis, as it postulates that external factors can influence LS and lead to increased or decreased LS. Certain external factors are of particular interest for us, as large-scale surveys have shown that age, gender, marital status, education, social relationships, and material well-being (household income satisfaction and satisfaction with standards of living) are important predictors of LS in high-income countries (Park et al., 2019; Dolan et al., 2008; Diener & Seligman, 2004). Hence, this section will seize the opportunity to use the social determinants of health framework and explain how specific predictors are associated with LS in the literature on the individual level, in high-income countries similar to Canada.

Gender differences in LS are well reported. Based on Gallup World Poll data from 2005 to 2014, Fortin and al demonstrated that, on a global scale, females tend to evaluate their LS as higher than males throughout all age categories (an average of 0.09 points higher on a 11-point Likert scale from 0-10), with the disparity being accentuated around age 30. For North America, Australia and New Zealand, this gap increased to an average of 0.17 points higher (Fortin et al., 2015). The effect of *age* on LS is also documented in the literature, with a gradual decrease in reported LS scores (on a global average, 0.6 points on a 11-point Likert scale from 0-10) from teenage years through midlife. Interestingly, in the North American region, data tends to show a U-shaped recovery in LS scores after ages 40 for men and 50 for women that mitigates the decrease experienced in earlier years (Fortin et al., 2015; Steptoe et al., 2014).

On the individual level, *socio-economic status* has also been found to influence SWB, specifically life evaluation (Diener, et al., 2010; Pinquart & Sörensen, 2000). Socio-economic status refers to an individual's status within society and is usually measured via a combination of income, social class, occupation, and education (American Psychological Association, 2021). A study done on the Gallup World Poll data, a large-scale sample representative of the world's population done in 132 countries, has found that there is a strong association between income and LS but less with the affective portion of SWB. This relationship seems to be mediated by one's satisfaction with their own standard of living (Diener, et al., 2010). This is in line with evidence that relative income – compared to our equals (in terms of job, socio-economic status, social circle, etc.) and compared to oneself in the past – and not solely absolute income is associated with well-being, although there seems to exist a threshold where absolute income directly impacts SWB (Clark et al., 2008; Frank, 2005; Luttmer, 2005; Clark & Oswald, 1996). Also positively correlated with income, *education level* also seems to be associated with SWB and LS through both indirect – due to health and income benefits – and direct effects. This association seems to be weaker than with income however (Pinquart & Sörensen, 2000; Dolan et al., 2008).

As discussed previously, *perceived good health status* has been shown to be positively associated with SWB – intuitively, it is generally accepted that poor health might lead to uncomfortable states and lack of opportunities to improve LS (Diener & Seligman, 2004). This association seems strongest when the participants self-rate their own health, as opposed to a rating provided by a third party (Okun, et al., 1984). The reverse is also true, as high reported SWB and LS are associated with better physical health (Diener & Seligman, 2004). Interestingly, in a cohort study recruiting more than 85,000 Ontarian adults, the odds of higher healthcare costs – i.e., being in the top 5% users of healthcare in terms of cost – for those with the lowest LS scores were 3.05 times higher (95% CI [1.161, 5.80]) than for those with the highest LS scores, adjusted for comorbidity score. This association was also observed for those who were middle users, i.e., the top 6-50% healthcare cost-generating users (Goel, et al., 2018).

Overview of public transit use in the Montréal Metropolitan Community

The population specifically studied in the Montréal arm of the INTERACT research program lives in part of the CMM, which includes the North and South Shores of Montréal, as well as the Island of Montréal itself (see Appendix I for a map of the CMM). The public transit infrastructure in the CMM is under the jurisdiction of the Metropolitan Regional Transportation Authority (ARTM; *Autorité régionale de transport métropolitain*), a regional government body in charge of the planning, organisation, and financing of public transit within the territory of the CMM (Autorité régionale de transport métropolitain, 2020). Its services include:

- the subway and bus system operated by the *Société de transport de Montréal* (STM);
- the bus systems operated by the *Société de transport de Laval* (STL) and the *Réseau des transport de Longueuil* (RTL); and
- the suburban rail network operated by *EXO.*

Data relating to public transit use specific to the CMM can be derived from the Origin-Destinations (OD) surveys performed every five years by the ARTM. This type of survey, common in transportation research, provides a detailed picture of the trips undertaken during an average weekday in fall within the territory of the CMM and within municipalities in the perimeter of Montréal for a random sample of households (Autorité régionale de transport métropolitain, 2020). The last OD Survey for the CMM was undertaken in 2018, reaching about 74 000 households, for a total of 170 000 individuals and 360,000 trips.

In a typical day, 9 426 000 trips (all modalities included) are made on the study territory – 2 497 000 of those at peak hour in the morning, with most being related to work (51% of total trips; 4% increase between 2013 and 2018) or school commutes (28% of total trips; 1% increase from 2013). 21% of work-related morning trips have a destination within downtown Montréal. However, a significant increase (12%) in morning work commute trips to the North and South Shores has been observed, highlighting the development of new patterns of transportation.

The proportion of motorized trips made at peak hour in the morning (by car/motorcycle, public transit or including both i.e., bimodal trips) increased by 1% from 2013 to 2018, whereas it had decreased in the previous cycle (2008-2013). Around 68% of morning commute trips are done by car or motorcycle. Nonetheless, we can observe an overall decrease in car/motorcycle trips compared to 2013 (-1% within the CMM territory; -4% on the Island of Montréal), and modest increases in public transportation (+4%), bimodal trips (+7%), and other means of collective transportation (+6%).

Gender seems to slightly impact public transit use, with women representing 54% of users (up to 56% of bus users). Young adults are also overrepresented: 52% of users belong to the 20–44-year-old age category, 23% belong to the 45–64-year-old age category and 7% belong to the 65-year-old and older category. Overall, 70% of users are less than 45-year-old – whereas they represent 53% of the population. Interestingly, occupation also seems to be associated with public transit use: workers (54% vs. 47% of the population) and students (36% vs. 22% of the population) are more likely to use public transit than retirees. This difference is especially notable for train trips, where 76% of users are workers.

Association between public transit accessibility and subjective well-being

Definitions and measures of accessibility

The concept of accessibility – specifically public transit accessibility – is multi-faceted. In its most basic semantic terms, accessibility refers to the ability to access something whether it is a location, a person, an activity, a service, etc. (Oxford University Press, 2021). Traditionally, within transportation studies, this is approached from a place-based perspective as the idea of proximity between two points in space, which can be weighted by economic, time or distance cost for the end user. Moreover, in real-world contexts, it is important to distinguish **accessibility** (the potential for interaction) from **mobility** (the realization of the potential for interaction, or in other words the ability to move through space and time) (Miller, 2018; El-Geneidy & Levinson, 2006). For example, by moving closer to work, one may increase their access to work, or their potential to access desirable locations, without necessarily changing how far they can go from their house. The two concepts are not necessarily mutually exclusive however: accessibility requires some degree of mobility.

Several operational definitions of the construct have been proposed over the years. In 1959, Hansen proposed that accessibility be defined as "the potential of opportunities for interaction [spending time with a person or in a place]" i.e., "a measurement of the spatial distribution of activities about a point, adjusted for the ability and the desire of people […] to overcome spatial separation" (Hansen, 1959). Later, in the 1970's, Ingram defined accessibility as "the inherent characteristic (or advantage) of a place with respect to overcoming some form of spatially operating source of friction (for example, time and/or distance)", adding that this can be further divided into "relative accessibility" (i.e., the degree of connection measured for two locations on the same plane) and "integral accessibility" (i.e., the different connections, for a single location, to all points on the same plane) (Ingram, 1971). Moreover, Morris et al. (1979) explained the need for accessibility measures to be mode-specific to "a particular transportation system". These definitions reflect the theoretical approaches based solely on travel impedance prevalent at the time.

However, these early definitions of accessibility did not take into account the notion of specific demand and attractiveness of certain locations/opportunities compared to others, as well as individual choices made by people and households. Travel costs (whether it is time, money or effort exerted) and individual decisions, such as residential choice or mode preference, were recognized as highly influential in travel demand models and as a function of accessibility, rather than these specific variables being included within accessibility indicators themselves (Morris et al., 1979; Burns & Golob, 1976). As early as the 1970's, Koenig notably criticized prior measures of accessibility and proposed a behavioral approach for the calculation of perceived travel cost for urban populations for different transportation modes and for different categories of people grouped by age and possession of a car as the two factors that would impact this metric (Koenig, 1980). More recently, Miller (2018) argues that to integrate the demand-based component of travel, the concept of accessibility should combine both the potential for interaction described beforehand and the “attractiveness and/or magnitude of opportunities (i.e., the desirability of/opportunities for interactions […]”. This perspective plays into a shift to a people-based approach to accessibility,

Beyond the definition of the concept of accessibility itself, which differs from author to author, many measures are used to operationalize this construct. The simpler measurement methods solely use travel distance between two points, which is generally acceptable for walking accessibility, but may not be as accurate for other transportation modes. Travel time can and should be used as an alternative, but comes with its set of challenges, namely the fact that its measurement both depends on the mode of transportation and time of day – as well as local patterns of traffic activity and specific transportation policy in place – which can complexify accurate stable representation of this metric (Miller, 2018). Many different measures of access exist: Fuller et al. published a rapid review of transit access measures that yielded 19 different measures, which are either focused on access within a census geographic area (or a specific area), or to a specific spatial anchor point (e.g., an individual’s residential address). Three specific simple measures were recommended: the number of public transit stops within a 1 km walking radius, the number of public transit stops located in a Diffusion Area (smallest geographical area used by Statistics Canada for census purposes), and the distance to the nearest transit stop from an origin point (e.g., an individual’s residential address). Another more comprehensive measure, the Public Transport Accessibility Index, was also recommended – however, this measure requires in-depth Geographic Information Systems (GIS) expertise and is computationally intensive and, for those reasons, was not used in this study (Saghapour, Moridpour, & Thompson, 2016; Fuller, 2018).

As we’ve outlined earlier, physical accessibility does not tell the whole story when it comes to the relationship between transit and subjective well-being. More sophisticated indicators have been proposed to take into account some forms of cost associated with the trip and better reflect travel impedance i.e., the difficulty to get from one place to another (Transportation Research Board, 2021). Accessibility may be weighed by objective factors, like travel distance, travel time or monetary cost, or subjective factors, such as trip pleasantness or unpredictability of schedules. Because objective and subjective impedance are not perfectly correlated (Novaco et al., 1990) and have differential consequences on well-being specifically, both aspects should be addressed and incorporated into conceptual models of transit accessibility (Gray & Lucas, 2001; Novaco et al., 1990). Utility-based measures of travel impedance have been proposed as a way to include subjective impedance perceptions and capture individuals' preferences in complex public transit environments (Nassir, et al., 2016). However, the complex methodologies lead to difficulties in interpretation for researchers and policymakers (Geurs & van Wee, 2004).

Public transit and life satisfaction

Increased accessibility, by public transit or other means of transportation, is thought to enable people's interactions with other people and within their communities to perform activities fundamental to their personal fulfillment, which in turn may increase individual LS. Despite this, few studies explore the relationship between public transit and SWB and, more specifically, LS. Most of the current data focuses on commuting times and modes, rather than transit accessibility. Therefore, the next section will expose relevant literature on both topics.

Association between commuting and LS

In their recent critical review on the subject, **Chatterjee et al***.* (2020) offer an overview of current evidence of the effects of commuting on subjective well-being. In this study, well-being is structured conceptually around three different periods: during the commute episode, immediately after the commute episode and over a longer period. As opposed to travel in general, which can be done for leisure purposes, commuting is described as "regular, unavoidable activity which absorbs substantial personal time and resources" and may have a hypothetically different relationship with SWB. Although multiple facets of the association are discussed in this review, we will focus on overall subjective well-being (the main outcome of the current study).

The first section of the review discusses the affective impacts of commuting. They argue that the concept of control is central to the affective experience of commuters and that increased impedance (and thus decreased subjective accessibility as described earlier) causes a loss of control that leads to stress. That control can be operationalised in different ways, as behavioural control i.e., the ability to make choices that impact the commute experience (e.g., having a flexible work schedule or choosing parameters of the transit environment like less crowded modes or times), or cognitive control (e.g., having a sense of predictability during the commute). In a broader way, commute stress is also dependent on internal factors such as gender. Chatterjee et al. underline the evidence that commuting by public transport is reported to be an "unpleasant and not arousing" experience with lower overall affect in bus commuters compared to drivers or cyclists. However, that experience may be influenced by length of commute and stress felt during the commute.

The second section of Chatterjee's review discusses the impact of commutes on LS, arguing that travel modes are strongly correlated with commute satisfaction (seen as a sub-component of overall LS and SWB). Public transit commuters report the lowest levels of commute satisfaction compared to other modes in Canada, Sweden, and China, although it is unclear if there is any differentiation between specific public transit modes. Commute length is negatively associated with satisfaction, as is travelling in the peak hours for public transit users in Sweden. The concept of control and choice is again discussed in relation to commute transit. Attitudes towards the commute affect satisfaction with the commute, with those reporting liking a particular mode and using it for regular commute having higher commute satisfaction, suggesting that a mismatch between mode preference and mode taken may lower satisfaction (e.g., a low-income individual with a low income may be limited to taking public transit because of financial constraints). The authors also discuss the role of commute within the broader context of LS, showing the existence of spill-over effects from the commute to other life domains. Literature suggests that long commutes may be associated with lower satisfaction with leisure, work, and social relationships. Despite this, evidence does not establish a consistent causal association between commuting and LS, as most of the data originates from cross-sectional surveys and contradicting conclusions abound.

A systematic review by **Norgate et al.** (2020) reviewed evidence from 1972 to 2017 and identified only eleven (11) studies linking commuting to affective experience and SWB – most relating to affective appraisals (which is out of the scope of this literature review). Of note, one British study using the longitudinal British Household panel Survey data found that, among 17 985 adult commuters, switching from commuting by public transit or car to active travel was associated with a mean improvement of 0.537 point on the General Health Questionnaire-12 scale, which measures psychological distress (Martin et al, 2014). Moreover, four (4) studies that focused on the association between LS with commuting were identified, although the majority of these identified affective experiences or satisfaction related to commute as an exposure. Only one study directly involved an exposure related to transit accessibility, which will be discussed in greater detail below (Stutzer & Frey, 2008).

Stutzer and Frey (2008) used subjective well-being data collected between 1985 and 2003 by the German Socio-economic Panel (*n* = 19 088 participants, leading to 39 141 observations) to assess if there was a correlation between participant' one-way commuting time and reported life satisfaction. LS was captured by reported agreement to the question "How satisfied are you with your life, all things considered?" on a 11-point Likert scale ranging from "Completely dissatisfied – 0" to "Completely satisfied – 10". According to this study, considering individual socio-demographic characteristics such as age, sex, and employment, an increase of one hour in commuting time leads on average to a 0.28-point decrease in reported LS. An increase in 1 standard deviation (18 minutes) leads to a 0.09-point decrease in reported LS on average. Moreover, there seems to be a larger negative effect of commuting for one hour via public transit versus via car, but this difference is not statistically significant. As exposed many times throughout this chapter, life satisfaction is a complex concept, and some unobserved factors that affect both the predictor and the outcome might bias current results.

Clark et al. (2020) examined the impact of workers' commuting time and mode on SWB, and more specifically on LS and LS specific domains such as job satisfaction and satisfaction with leisure time. This longitudinal study using the six waves of Understanding Society data (collected from 2009 to 2014) followed a sample of over 26 000 English workers. The authors showed through correlated random effects regression models that, for the same individual, one-way commute time in minutes is negatively associated with decreases in job satisfaction (-0.0011, $p < 0.01$) and leisure time satisfaction scores (-0.0030, $p < 0.01$) in the overall sample especially for job satisfaction in women, although that was not the case for young adults and lower income individuals. Between-individual variation followed the same patterns with statistically significant negative association between commute time and job (-0.0020, $p < 0.01$) and leisure satisfaction (-0.0021, $p < 0.01$). There was no significant association with overall LS. Interestingly, bus/metro use showed a statistically significant relationship with LS at a 90% significance level within individuals (-0.0786, $p < 0.10$). This relationship is also statistically significant when comparing participants (-0.1411, $p < 0.01$). Moreover, results show that the relationship between commute time and LS may be mediated through a LS sub-domain, leisure time satisfaction. Longer commute times lead to reduced leisure time satisfaction, which in turn is associated with decreased LS. Limits of this study include the fact that the available panel data did not provide detailed information related to commuting frequency and the occurrence of multi-modal commuting trips, as well as some important variables that have been demonstrated to influence the relationship between commuting and SWB, like perception of transit, mode preferences and so forth.

Association between public transit accessibility measures and LS

A small survey study done by **Cao** (2013) in the Minneapolis-St. Paul metropolitan area (United States) investigated the association between LS and perceived access to a light rail transit called the Hiawatha line. The author compared the Hiawatha light rail transit line area to two other similar urban corridors without light rail access in the same region (Nicollet and Bloomington Avenue), as well as two suburban corridors with limited access to transit (Coon

Rapids and Burnsville). Perception of built environment characteristics were measured by indicating agreement with statements about different characteristics on a 4-point Likert scale, creating composite indicators for both accessibility and transit access (including easy access to transit stop and quality of public transit service). LS, which was one of three outcomes studied, was assessed using a composite score derived from a version of the Satisfaction with Life Scale (Diener et al., 1985). Participants were randomly sampled from two different databases of residents who were either already residents of the area before the opening of the Hithawa line in 2004 (the "nonmovers") or those that had moved after the opening of the line (the "movers"). Overall, around 2 000 addresses from the Hiawatha corridor and 4 000 from the other four corridors were selected, out of which 5 884 were valid (response rate = 22.2%; final sample size: n = 1 303). Compared to the 2010 United States Census data, the sample was overall representative of the population studies, although homeownership rates were higher than those reported in the Census with underrepresented households with children and slightly smaller household size in all four areas. Through a structural equation modeling (mediation) approach, standardized direct effects were estimated. Perceived access to public transit had a statistically significant positive association with satisfaction with travel (0.081, $p < 0.05$) and overall accessibility perception with LS (0.108, $p < 0.05$). However, the relationship between transit perception and LS was not assessed. A limit of this study is the existence of concurrent built environment improvements in the areas studied, which could have led to increased accessibility and biased the associations studied.

In Arizona (United States), **Pfeiffer et al.** (2020) used survey data to examine the association between three domains of built environment (access to green spaces, walkability, and transit) and SWB in the metropolitan Phoenix area, an area described by the authors as "a prototypical American suburban region, defined by expansive single-family subdivisions, dendritic street patterns, and commercial strip malls". Only the transit-related data will be discussed within this section. Using mail-in questionnaires, among other exposures, transit was assessed objectively using the AllTransit™'s 2019 Transit Connectivity Index and subjectively by measuring agreement with the statement "It is easy to walk to a transit stop, either bus or light rail, from my home". The natural log was used for all calculations as few participants lived in high-transit neighbourhoods. LS was assessed using a composite score derived from a version of the Satisfaction with Life Scale. Several individual (age, household income, education, race and home ownership) and neighbourhood (neighbourhood stability, linguistic diversity, and poverty) characteristics that could potentially affect SWB were treated as covariates. Participants were selected at random based on United States Postal Service addresses, using stratified random sampling within 12 census tracts chosen to represent the diversity of built environment types in the area (response rate = 39% [22-56%]; final sample size: $n = 475$ with complete values for life satisfaction). According to the authors, respondents' demographics were overall in line with their own census tracts for age and household incomes; they were however more likely to have graduated college (29% vs 23%) and less likely to identify as Hispanic (20% vs 37%). 47% of respondents felt that they lived in an area with accessible public transit, although on average, they lived in areas with low objective public transit accessibility. On average, older Caucasian people who reported higher income and were college-educated reported higher LS, independent of transit availability, compared to other groups. Ordinary least squares regression was used to assess the associations between transit and LS. The authors show a weak negative association between objective transit accessibility and LS (-0.016, $p = 0.05$) after accounting for covariates. The authors underline that accessibility to transit includes more than walkability (what was assessed by the study), but also route frequency, diversity of modes available, etc. Of course, other individual factors such as personality or health could mediate the association between transit access and life satisfaction, as discussed previously.

Current knowledge gaps

From the studies outlined in this chapter, it is possible to identify several knowledge gaps in the current literature on the association between public transit accessibility and SWB that merit further exploration. Most studies assessing the relationship between public transit accessibility and well-being focus on commuting or trip satisfaction, both during the trip and after the trip, whereas the focus of our study will be on LS on a longer time horizon. The literature is currently equivocal about the relationship between public transit accessibility and LS – therefore this study might add to the currently available corpus of evidence.

Additionally, current objective measures of accessibility do not consider the fit between utilitarian travelling needs for daily activities and current public transit offerings based on individual high-fidelity data. This could provide insights to guide mode switching initiatives spearheaded by transit agencies. Finally, of those studies that do evaluate transit accessibility and well-being, most are done in large European cities, or in American cities with low transit access, contexts that are different in Montréal.

Chapter 3: Methods

This chapter describes the methods used in this study. Then, the exposures and outcome of interest as well as the covariates chosen will be described, including an explanation of how they were measured in this current study. Finally, we provide details about the statistical and sensitivity analyses.

INTERACT research program: subject selection and data collection tools

Data comes from the 1st wave of the Montréal arm of the INTERACT cohort study, collected from Spring to Fall 2018. Recruitment was done mostly via bilingual French and English social media ads (Facebook, Twitter), but also traditional media coverage and in-person recruitment campaigns at strategic public events on the Island of Montréal as well as in Laval and on the South Shore of Montréal (e.g., festivals, cycling events, etc.) (Wasfi, et al., 2021). In some cases, outreach activities were organized with various community groups to increase participation of under-represented groups (older adults, specific neighbourhoods, etc.) and aid in filling out the questionnaires for these populations.

Individuals were invited to fill out an eligibility questionnaire online. Inclusion criteria were being 18 years old or older, living in a defined portion of CMM (i.e the Island of Montréal, Laval, Longueuil, St-Lambert, and Brossard – see Appendix II for a map of included municipalities) and reporting leaving home at least once a week. Exclusion criteria included being younger than 18 years old, being unable to read or write French or English with enough proficiency to fill out the needed questionnaires, and planning to move out of the region within the next two years (Kestens, et al., 2019).

To collect data, the longitudinal study uses three modalities: the Montréal INTERACT questionnaire, the VERITAS-Social (Visualisation, Evaluation and Recording of Itineraries and Activity Spaces) map-based survey (Chaix, et al., 2012; Naud et al., 2020), and an app-based GPS

(ETHICA) and accelerometer data recording (SenseDoc) (Kestens, et al., 2019). This study uses data from the 833 participants who completed the VERITAS questionnaire.

The VERITAS questionnaire is especially important, as it is the main source of information for geospatial coordinates for key locations (including residential address) used to assess public transit accessibility. This questionnaire is a self-administered interactive map-based survey. Using a marker on the map provided by the Google Maps Application Programming Interface (API), participants were asked to identify their residence, as well as other locations of interest where they regularly performed certain activities (e.g., work, study, errands, and other types of shopping, leisure activities – see Appendix III for a list of all locations questioned). They were also asked to indicate the frequency of visit to each location (number of visits per week/month/year), as well as the transportation modes usually taken. Other information, such as social networks, was also recorded but not used in the context of this study (Chaix, et al., 2012; Team INTERACT, 2021). This tool was validated by a 2018 study showing that there is a good correspondence between data collected via VERITAS and 7-day GPS tracking (Kestens et al., 2018). Of note, not all participants signed up and consented for GPS data collection : 563 participants provided data through the EthicaData app and 163 wore a SenseDoc device.

Exposures of interest: transit fit measure and public transit use frequency

The main exposure of interest, the transit fit measure, aims to quantify how public transit offerings meet, or in other words, fit, with an individual's transportation needs, knowing their destinations. It is an individual travel time ratio measure (thereafter called the transit fit measure) and was constructed using real participant self-reported travel data, as well as open-access time and distance data. The development of this novel measure – including theoretical basis, results, and face validity assessment – is described in more details in Chapter 4.

A secondary exposure, the frequency of public transit use was calculated on an annual basis. It measures the number of public transit trips taken by an individual, based on self-reported transit use data (days travelled per season) for each participant. This was assessed by asking the question “How often do you typically travel by public transit during each season?” for fall, winter, spring, and summer. The sum of frequencies for all seasons was calculated and collapsed into four categories: “Non-users” who never take public transit (0 days/year), “Low users” (< 1 days/week, or 1-51 days/year), “Medium users” (1-4 days/week, or 52-259 days/year) and “High users” (≥ 5 days/week, or ≥ 260 days/year). Category thresholds were decided based on logical cut-off points, context-specific to the collected data.

Auxiliary exposures of interest: geographic accessibility to transit

Walking accessibility of transit was also measured to describe the current portrait on the territory studied by INTERACT, as well as to help to validate the newly created transit fit measure. Geospatial analyses needed to measure geographic accessibility to transit were performed using the open-source software QGIS (QGIS.org, 2021). The OpenStreetMap map and road network were extracted on September 27, 2020 (OpenStreetMap contributors, 2020). Roads fit for walking and pedestrian use were considered for the geospatial analysis: highways and service lanes were excluded from the final road network. From these files were extracted the road networks for Laval, Montréal, and the South Shore of Montréal (Longueuil, St-Lambert, and Brossard) where INTERACT participants reside. The walkable street networks were exported into shapefiles (*.shp) and overlaid onto the OpenStreetMap map layer.

General Transit Feed Specification (GTFS) data was downloaded from the RTL and STL websites to extract the coordinates for the location of bus stops for Laval and the South Shore, which were then exported into shapefiles (*.shp) (Réseau de transport de Longueuil, 2020; Société des transports de Laval, 2020). GTFS data was also extracted from the EXO website to extract the coordinates for the location of all train stations on the territory studied (EXO, 2020). Those coordinates were extracted into shapefiles (*.shp) and manually checked with Google Maps Street View to accurately ascertain possible entry points into the train stations and adjust geocoded locations if necessary. Each transit access point (bus stops and metro/train station entry points) appeared as a single point on the map, on separate layers depending on the mode of transportation.

The data was divided into different areas using regional boundaries to maximize computational efficiency of geospatial analyses. Two different types of accessibility metrics were calculated, for which the methods used are explained below: the walking distance to the nearest transit stop and the number of stops within walking distance (1 km from the participant's residence). This choice of metric was based on ease of use, and on the previously presented literature review – especially the results of a Flash Review of transit access measures published by the INTERACT team in 2018 (Fuller, 2018).

We calculated the shortest distance from home to a transit access point using the Network Analysis tool in QGIS. This process was done in three phases, once for each mode. These distances were treated as continuous variables in the models. Density of public transit stops around each home address was computed within 1-km network buffers around each place of residence. QGIS' Intersection feature (in the Geoprocessing tools) was used to identify transit access points that fell within each buffer. Again, this process was repeated for each mode. All data outputs were exported into excel documents (*.xlsx) and imported in R for statistical analysis.

Outcome of interest: well-being measure

The Personal Well-being Index 5th Edition (PWBI) was used to measure subjective well-being (International Wellbeing Group, 2013). The PWBI's 5th Edition is the fruit of an international collaboration involving over 150 researchers from all over the world.

The PWBI is a self-administered multi-item scale which aims to measure well-being through seven (7) core items of satisfaction within various quality-of-life domains (standard of living, health, life achievement, relationships, safety, community-connectedness, and future security) to ultimately answer the question: "How satisfied are you with your life as a whole?".

Two (2) optional items of satisfaction (general life satisfaction and spirituality/religion) were also included, but not integrated into the final PWBI score, as recommended in the 2013 PWBI Scoring guidelines. Indeed, this item may present disordered response thresholds and may not adequately capture the desired construct in Australian and Canadian populations (Misajon et al., 2016).

Each item is rated on a 11-point Likert scale ranging from “No satisfaction at all - 0” to “Completely satisfied - 10”. The domain scores (excluding general life satisfaction and spirituality/religion) are then summed to create an average subjective well-being score for each participant – the Personal Well-Being Index – which can be converted to a 0-100 scale by multiplying the resulting score by 10. Of note, the expected normative range for the mean PWBI score in Western populations is 70-80 (*mean*: 75.23, 95%CI [73.78, 76.68]) (International Wellbeing Group, 2013).

Covariates

Information about car ownership and general access to a car were included in the models, as this may impact public transit use level and vice versa (Holmgren, 2020; Kim & Kim, 2005; Kitamura, 1989). As described in the literature review (Chapter 2), sociodemographic characteristics like age, gender, socioeconomic status, and physical health are important predictors of well-being – and were included as covariates. We used the education level as a proxy of socioeconomic status, because it is a component of socioeconomic status and income data was absent for a majority of participants (American Psychological Association, 2021).

Car ownership and access to a car

To capture car ownership and access within the household, participants were asked the question “How many cars, trucks, or vans are kept in your household?”. The answers were collapsed into “Non-car owner” (if the answer was 0) and “Car owner” (if the answer was ≥ 1).

A measure of access to a car, whether by owning a vehicle, having access through their household or having access through outside means (carsharing, renting, etc.) – further included responses to the question "Do you have access to a car kept outside of your household?" with the following possible answers: "Yes, I borrow a friend's or relative's car", "Yes, I am a member of a car-sharing program [Communauto, Car2go, etc.]", "Yes, for another reason (Please specify)" and "No, I do not have access to a car kept outside of my household". This variable was then collapsed into two categories, either "Access to a car" (> 0 cars/trucks or vans within the household and/or access to a car outside the household) and "No access to a car" (0 - or NA answer – car/truck/van within the household and negative answer to question about access to a car outside the household) accordingly.

Age

Participants' age at the date of survey completion was calculated based on the Health Questionnaire's completion date and the date of birth. Age was used as a continuous variable.

Gender

Participants' gender was collected in the Health Questionnaire with the following possible answers to the question 'How do you identify?', with options including "Man", "Woman", "Trans man", "Trans woman", "Genderqueer/Gender non-conforming" or "Different identity" to specify. The categories were then collapsed into "Man" (including those who identified as trans men) and "Woman" (including those who identified as trans women). The participants who identified as either genderqueer or a different identity were excluded from the final sample, because of concerns due to the small numbers of complete cases (i.e., cases with no missing values) within those two categories.

Education level

The participants' education level was assessed by asking the question "What is your highest education level?" with the following ordered answer choices: "1: Primary/Elementary school", "2: Secondary school", "3: Trade/Technical school or college diploma", "4: University degree", "5: Graduate degree", and "-7: I don't know/Prefer not to answer". The answers were collapsed into two categories: "Non-university-level degree" (choices 1 through 3) and "University-level degree" (choices 4 and 5). Only one participant in this sample chose to not disclose his education level and was included in the "Non-university-level degree" category.

Physical health

Physical health was assessed through the 12-Item Short Form Health Survey (SF-12), a validated self-completed (i.e., completed by participant) multi-item scale derived from the Medical Outcomes Study 36-Item Short-Form Health Survey (SF-36) and used to assess subjective general health outcomes and their impact as experienced by the patient (Ware, Kosinski, & Keller, 1996; Turner-Bowker & Hogue, 2014). Eight different domains are covered, namely: physical functioning [limitations in physical activities due to health problems], vitality, role-physical [limitations in usual roles due to physical health], bodily pain, general health, social functioning, role-emotional [limited in usual roles due to mental health], and mental health.

A physical component summary score (PCS-12) was used as a proxy of physical health for this study. A scoring algorithm is applied to transform scores to have a mean of 50 with a standard deviation of 10, based on the United States population distribution (i.e., norm-based scoring). A higher score indicates better reported physical health. The PCS-12 was used as a continuous variable (Turner-Bowker & Hogue, 2014).

Statistical analysis

The statistical analysis of the data involved descriptive statistics and multiple linear regression models using cross-sectional data. Analyses were conducted using R Version 3.6.1 from October 2020 to May 2021 (R Core Team, 2017). Data was cleaned and formatted using multiple R packages including tidyverse. Descriptive statistics were performed using base R functions and data visualizations were created using the ggplot package. To characterize the association between accessibility to public transit and indicators of subjective well-being, we ran multiple linear regressions models using base R (lm function). Models controlled for the actual frequency of public transit use and the following covariates: car ownership, age, gender, education level, and physical health.

Sensitivity analyses

Sensitivity analyses were performed to assess the impact of certain methodological choices that were made. This includes replacing the original transit fit measure (described in the next chapter, Chapter 4) by the following alternative versions of the original measure:

- a transit fit measure categorized as a binary variable: adequate fit with lifestyle (yes or no) (threshold at 3.03, i.e., mean + 1 SD); and
- a transit fit measure calculated using only home-work journeys.

Moreover, a sensitivity analysis of one of the exposures – the annual frequency of use of public transport – treated as a continuous variable, instead of a categorical value as in the main models, was done to assess if the arbitrary categorisation chosen affected the main effects derived from the regression models. As the transit fit measure is a novel metric developed in the context of this thesis, it was deemed interesting to compare our findings with those obtained with more “traditional” accessibility measures (i.e., number of public transit stops within 1 km, as well as distance to nearest bus, metro, and train stop for each individual).

Chapter 4: Development of an individual travel time ratio measure to approximate public transit accessibility

This chapter will discuss the development of the transit fit measure. This measure is a ratio of the time needed to carry out a trip between the participant 's home and regular destinations using public transit (numerator) and car travel times for the same trip (denominator). The transit fit measure is designed to simplify the comparison of time cost for two transit modes and approximate accessibility to key locations.

Use of open-access data for transit accessibility measures

As shown in the earlier literature review (Chapter 2), current measures of transit accessibility are imperfect at best and often require in-depth specialized GIS knowledge and capacity to be understood. However, the interest in the relationship between transit accessibility and health outcomes (including SWB) is increasing as authorities spearhead the "Health in all policies" approach as a health promotion tool.

Using readily available open-access tools such as the Google Application APIs may help reduce reliance on computationally intensive GIS models, especially when this specialized technical expertise is not available. Simply put, an API is a software intermediary that enables a user (the developer) to request specific data from a given application and provides the requested data in a usable form. One of the advantages of using an API is that the computation resources are linked to the infrastructure where the application is housed – that is, the computations are not performed on a local computer but remotely. As an example, the Google Distance Matrix API acts as an intermediary between the end-user and the Google Maps data housed: all requested calculations are performed on Google's servers, providing additional flexibility to researchers who lack access to technical or computational capacity. Another advantage is that information provided by the API is often updated far more regularly than usual static data files, thus enabling researchers to have a dynamic and current data source that is easily accessible without licensing or specialized software. This is especially important for transit time calculations, which depend on a multitude of rapidly changing parameters: traffic patterns, road closures, changing routes, etc.

Improving ease-of-use could potentially lead to increasing use of public transit accessibility measures within the health research field. However, this is conditional upon the validation of such a metric. So far, few studies have presented the development of new transit accessibility metrics based on open-access databases. A recent publication used a combination of real-time traffic and GTFS data, road network files from OpenStreetMap, as well as estimated travel demand via density of geotagged Twitter data to calculate a travel time ratio comparing trip duration for public transit and car in four cities - São Paulo, Stockholm, Sydney, and Amsterdam (Liao et al., 2020). More directly applicable to our context, Haitao et al. (2019) presented a new approach to measure walking accessibility to public transit service stops, using gridded cells' centroids of the given study area to compute walking distances to the nearest transit stop. This measure was then validated by comparing it to the number of nearby transit access points (commonly used as a proxy of public transit accessibility as discussed in Chapter 2) using open data for the Beijing area, which showed a strong negative correlation (r = -0.326; R^2 = 0.780).

However, all cited literature focuses on aggregate measures of accessibility which do not consider real destinations that are frequented. As underlined by the literature review in Chapter 2, accessibility is not only a function of geography and physical distance, but also depends on the fit between an individual's needs and the transportation options that are accessible to them based on their available resources (physical, mental, monetary, etc.). This highlights the need for a specific measure of transit mode fit which compares the accessibility of different destinations via multi-modal public transit versus by car using high-precision location data on the individual level, the development of which will be explained below.

Methods: methodological choices and calculation procedure for the transit fit measure

The Google Distance Matrix API was chosen for the purposes of this study, as it was versatile and able to easily provide time and distance values for given origin-destination trips, for multiple transit modes.

To maximise computational efficiency and to reduce costs, a finite number of location types was used. Location types were selected to reflect basic daily commuting patterns frequently performed by most participants. To do so, relative weights to rank locations categories and choose those that were frequently visited by most participants were calculated by multiplying the number of occurrences of said type of location in the sample by the mean annual frequency of visits (in number of days per year) for each category. Based on the results shown in Table 1, we chose to include home, work and supermarket locations reported by participants. Public transit locations were excluded as they are taken into account in the measure. It was assumed that participants are at their home 365 days per year, to simplify calculations as days spent out of the primary home were not recorded.

***Table 1** : Number of locations reported, mean annual frequency of visits and attributed weight (number of locations reported x mean annual frequency of visits) by type of location recorded in the VERITAS questionnaire (INTERACT, Montréal, wave 1, 2018) – sorted by weight*

Locations	Number of locations reported	Mean annual frequency of visit (in days/year)	Weight
home	833	365	304 045
public transit	1 624	111	180 264
work	740	198	146 520
supermarket	2 205	59	130 095
leisure physical	947	94	89 018
walk*	921	94	86 574
park	1 031	72	74 232
other locations	641	63	40 383
restaurant/food est.	1 579	25	39 475
specialty food store	711	40	28 440

convenience store	466	58	27 028
bakery	621	43	26 703
drugstore	770	32	24 640
school	149	143	21 307
liquor store	697	26	18 122
public market	427	39	16 653
volunteering	262	58	15 196
cultural leisure	704	16	11 264
bank	464	24	11 136
restaurant take-out	491	20	9 820
other residence	105	92	9 660
religious	62	110	6 820
post office	472	12	5 664
hair salon	528	7	3 696
doctor or HCP	734	4	2 936

* Location where participants report going on a leisure walk specifically (e.g., parks, circuit, etc.)

Because the VERITAS questionnaire focuses on measuring activity-spaces by asking about destinations and frequency of visits, there was no information about specific origin-destination trips per se. To overcome this hurdle, a matrix of all possible unique origin-destination (O-D) pairs for home, work and supermarket locations reported by a participant was created. All duplicate pairs were removed from the matrix. Trips that mirrored another O-D pair were also removed as the travel time was the same for both in a small sample of 10 participants. For example, if the matrix already contained a home-work trip, the reverse trip (from work to home) was removed.

We used the gmapsdistance package in R (Azuero et al., 2020) to access the Google Maps Distance Matrix API via Hypertext Transfer Protocol Secure (HTTPS). This API retrieves times and distances for specific queries. This specific R package was chosen for its ease of use, as well as previous use in health geography research (Sommerhalter et al., 2017; Macdonald et al., 2019; Mentias et al., 2020), as well as for public transit accessibility research (Haider & Donaldson, 2017; Heaney et al., 2019). This was used to calculate the drive time, as well as transit time for all O-D pairs in the matrix created. Transit information was available for the whole territory covered by the INTERACT study in Montréal. To maintain confidentiality, geospatial coordinates of all locations provided by participants were submitted to the API without any identifiable personal information through the HTTPS transfer protocol.

Other than location coordinates, requested parameters included day and time of the day that the trip was carried out. As the aim of the transit fit measure development was primarily to assess fit between participants' usual commute trips (lifestyle considerations) and transportation offerings, peak traffic hours in the Montréal area – 8:00 and 16:00 – were chosen to calculate trip information based on historical data from 2017 to 2020 collected by TomTom, a leading location technology developer (TomTom, 2021). The Google Maps Distance Matrix API does not support the use of past dates in its algorithm to calculate trip duration and the date provided needs to be in the future. Therefore, an arbitrary date (January 13th, 2021 – a Wednesday) was chosen. This specific date was chosen as it was in the middle of the week to minimize the odds of traffic data being affected by statutory holidays or different weekend traffic patterns. The information retrieved was then encoded into individual excel files for each participant, containing the geographic coordinates and frequency of visit for both the origin and destination points, as well as transit time and drive time extracted via the gmapsdistance package. From there, the calculation procedure went as follows:

1. Each origin-destination pair was assigned a weight based on the annual frequency of visit for both the origin (*freq.or /365 days*) and the destination (*freq.dest/365 days*) following the formula below:

$$\frac{\text{freq.or*freq.dest}}{365^2}$$

This method yields a table that resembles Figure 1 below for each origin and destination combination.

or	freq.or	dest	freq.dest	Time$transit	Time$driving	ratio	weights
	365		260	2040	1560	1.3077	0.7123
	365	 1	52	840	480	1.7500	0.1425
	365	 2	52	660	240	2.7500	0.1425
	365		4	540	360	1.5000	0.0110
	260	 1	52	1680	1440	1.1667	0.1015
	260	 2	52	1620	1560	1.0385	0.1015
	260		4	1800	1560	1.1538	0.0078
 1	52	 2	52	420	420	1.0000	0.0203
 1	52		4	420	240	1.7500	0.0016
 2	52		4	180	180	1.0000	0.0016

Figure 1 *: Example of a table created for a participant to calculate the transit fit measure*

2. A weighted mean of all time ratios for all the selected trips is then calculated following the formula below to yield the transit fit measure, one for a trip carried out at 8:00 and another for a trip carried out at 16:00– again for each time parameter value (8:00 and 16:00 in this study):

$$\frac{\sum_{i=1}^{n}(x_i \ * \ w_i)}{\sum_{i=1}^{n} w_i}$$

3. Finally, an average of the transit fit measures calculated for the two peak traffic hours was then calculated.

Descriptive statistics

The transit fit measure was calculated for 811 of the 833 participants who filled out the VERITAS and for whom geocoded location data were available. Calculations could not be done for 21 participants. 6 participants only reported their residential address, and no work or supermarket location. Only partial itinerary data was available for the other 15 excluded participants.

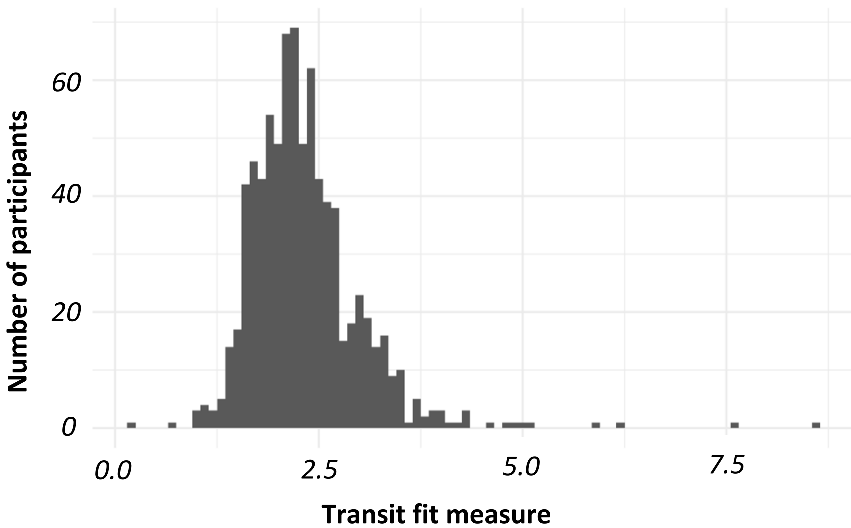

***Figure 2** : Distribution of the transit fit measure*

The sample distribution of the transit fit measure approaches that of a normal distribution as shown in **Figure 2**, with the bulk of transit fit measures landing between 1.5 and 3. A few outliers are present at > 5. The mean transit fit measure was 2.38 (*median*: 2.27 with a minimum of 0.24 and maximum of 39.96), which means that, on average, a trip done using public transit took 2.38 times longer than by car. An alternative transit fit measure only accounting for home-work commuting gave a similar ratio of 2.27 (*median*: 2.13 with a minimum at 0.74 and a maximum at 19.67).

We can see on **Figure 3** that, interestingly, most individuals for whom the transit fit measure is between 1 and 2 live in mostly central neighbourhoods on the Island of Montréal or near public transit hubs in Laval and on the South Shore. However, those with transit fit measures above 2 seem to be evenly distributed with no clear discernable spatial pattern, although those with values above 3 seem to be found in suburbs. There are only 3 participants for whom the transit fit measure is smaller than 1 (i.e., for whom public transit is faster than driving).

Finally, the transit fit measure was compared to “traditional” public transit accessibility measures as described in Chapter 2, i.e., the shortest distance from the nearest public transit stop – for bus, metro, and train stations – and the count of stops within walking distance (1 km). As we can see from **Figure 4** through **Figure 7**, there does not seem to be a clear relationship between any of those accessibility metrics and the transit fit measure. Note that the outlier value at 39.96 was removed from all those figures for better visualisation.

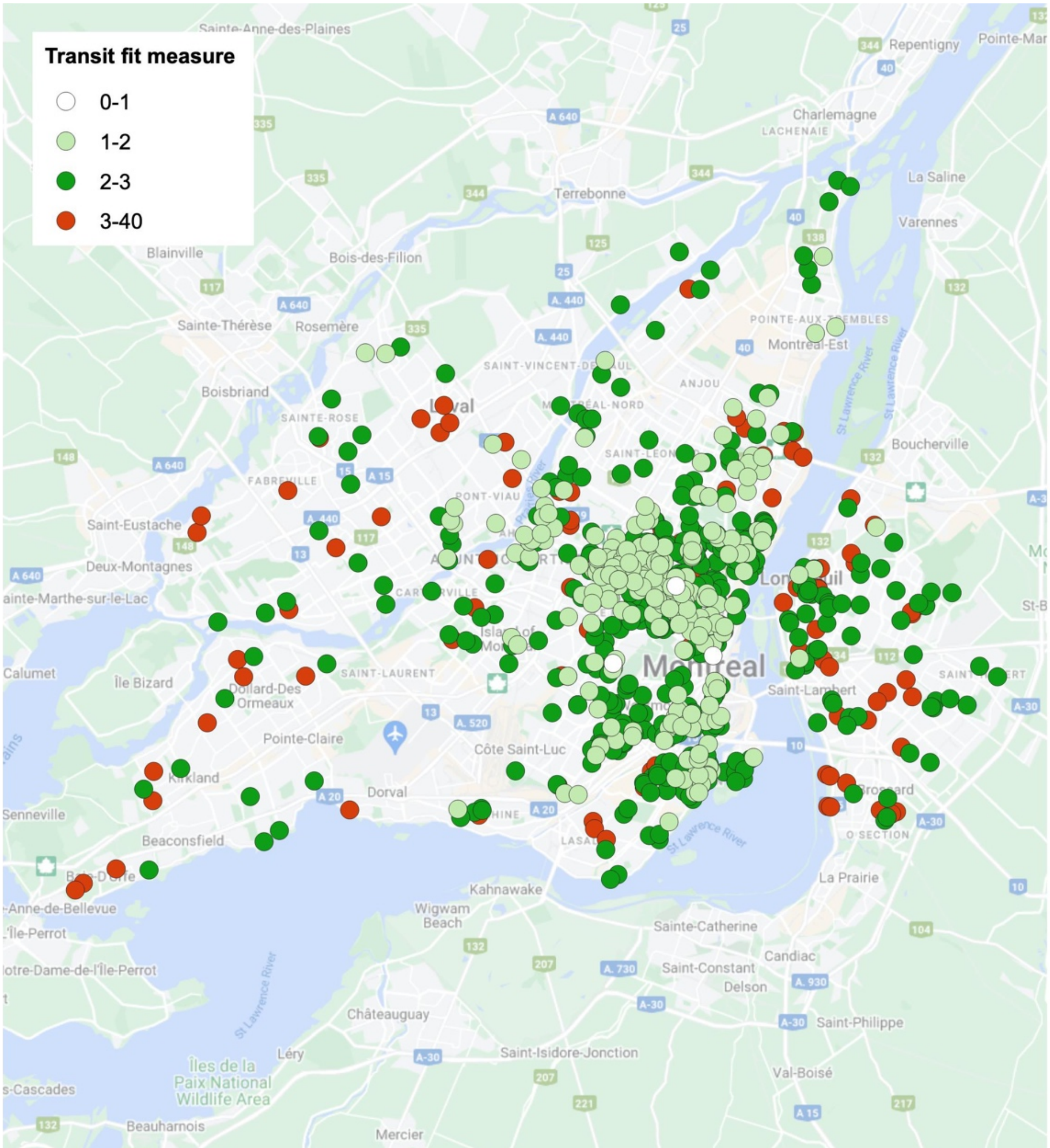

Figure 3 : *Participants' fit measure values, placed at their residential address (Map data © OpenStreetMap)*

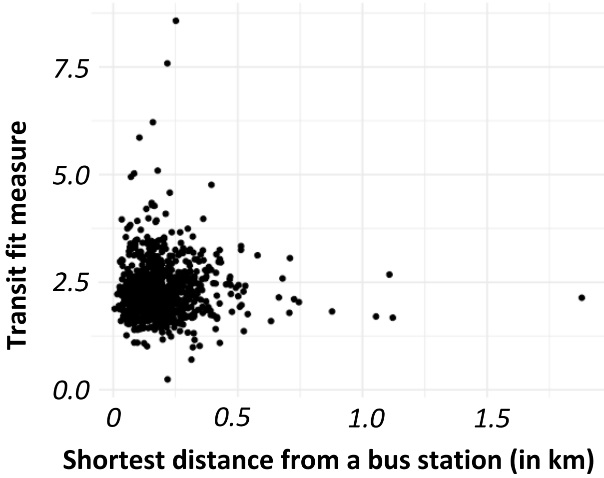

***Figure 4** : Scatterplot of transit fit measure depending on the shortest distance from a bus stop for each individual*

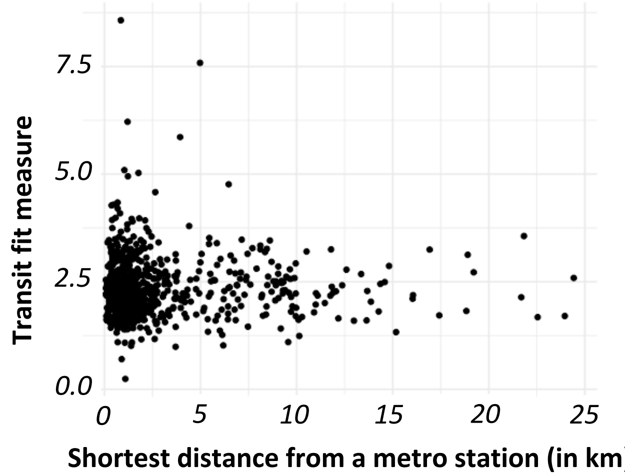

***Figure 5** : Scatterplot of transit fit measure depending on the shortest distance from a metro stop for each individual*

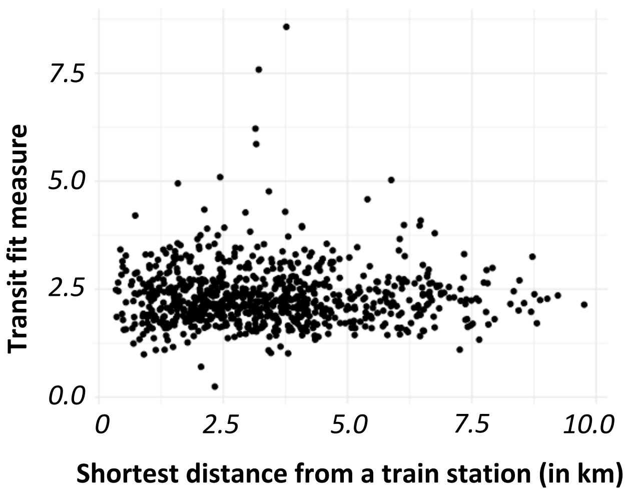

Figure 6 *:* Scatterplot of transit fit measure depending on the shortest distance from a train stop for each individual

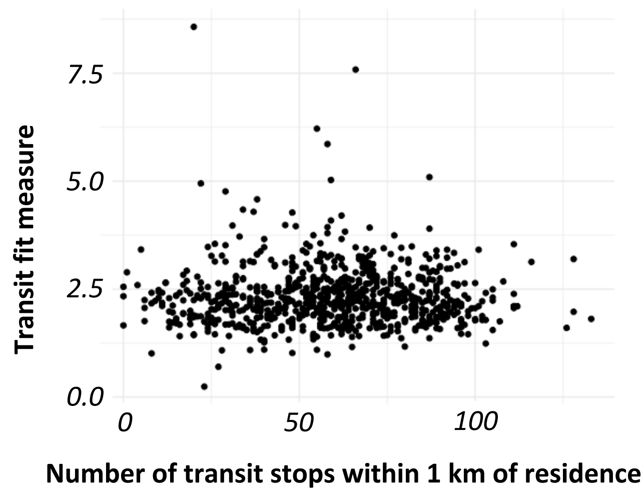

***Figure 7** : Scatterplot of transit fit measure depending on the number of transit stops within 1 km of residence for each individual*

Advantages and limits of the transit fit measure

There are several advantages to using the transit fit measure to try and quantify accessibility. This metric can be calculated without recourse to in-house specialized GIS technical expertise that may not be available to all researchers. Using a free R package to retrieve the data, the process is reproducible and can be scaled up or down relatively easily depending on the sample size used, with minimal coding knowledge and without the need for a specialized software license. The use of open-access high-quality data through the Google Distance Matrix API (the same data used on Google Maps on cellular phones) enables the researcher to access relatively recent traffic data accounting for possible ongoing roadblocks or major longer-term closings that may affect transit time, especially if used in a short timeframe after data collection. The procedure developed is versatile and can be adapted to accommodate more parameter combinations. For example, it is possible to calculate a transit fit measure for all hours of the day, or for multiple days.

One of the limits of this novel measure is the monetary cost of querying the Google Distance Matrix API for a high number of elements, which we attempted to minimize by optimizing the query algorithm used in R. A careful assessment of resources and GIS capacities should be made before incurring. However, this can be circumvented by minimizing the number of origin-destination pairs. Other free tools, such as OpenRouteService or OpenTripPlanner, could also be used for similar purposes.

As discussed previously, in our study, the data provided in the VERITAS questionnaire did not reflect specific trips made by the participants, as only locations visited as well as frequency of visits were collected. To approximate all possibilities, a matrix of all possible unique O-D pairs for home, work and supermarket locations reported by a participant was created, which led to an increased number of queries compared to what would have happened in reality. Additionally, the ”best” transit route chosen by Google to calculate transit time may not be the one that would be chosen by the participant, due to route preferences and other concerns, such as numbers of transfers, time spent walking, etc. A solution to this problem could be to adapt VERITAS to ask for all possible origins when identifying a destination, which was done for the RECORD study (Chaix, et al., 2012), but not for INTERACT. GPS data could also be used to better reflect actual trips made by participants. However, other issues may appear, such as limited participation due to privacy concerns, need for specialized expertise to analyse GPS data, and deployment cost if auxiliary devices are used.

Another limit of this measure is that regular updates in API may be difficult to track for end users, which could have had an impact on the data retrieved if this is done in batches. The algorithm used to predict transit time is proprietary. In addition, the API can only return data for the analysis date or for future dates. As the distance and time for each trip was calculated by the Google Maps API for January 2021 (more than two years after data collection), there is a possibility that these parameters were underestimated compared to the real parameters for trips recorded by participants in 2018, as workplaces and post-secondary schools were closed in 2021. It is especially true for car trips as road traffic decreased and could bias the measure away from the null. Finally, the method used does not consider the time spent looking for parking when using a car and thus systematically underestimates the denominator of the measure. It also doesn't include any costs associated with transit (transit fares that may be different according to modalities) or car use (car costs, gas, parking, or valet fees, etc.).

Chapter 5: Results

This chapter will first describe the composition of the final sample regarding data collected and main socio-demographic characteristics, including participants that were excluded and the reasons why they were excluded. Then, descriptive statistics pertaining to the geographic accessibility to public transit, as well as its use and covariates in the study sample will be discussed. Finally, the results of the regression models performed will be detailed.

Description of the study sample

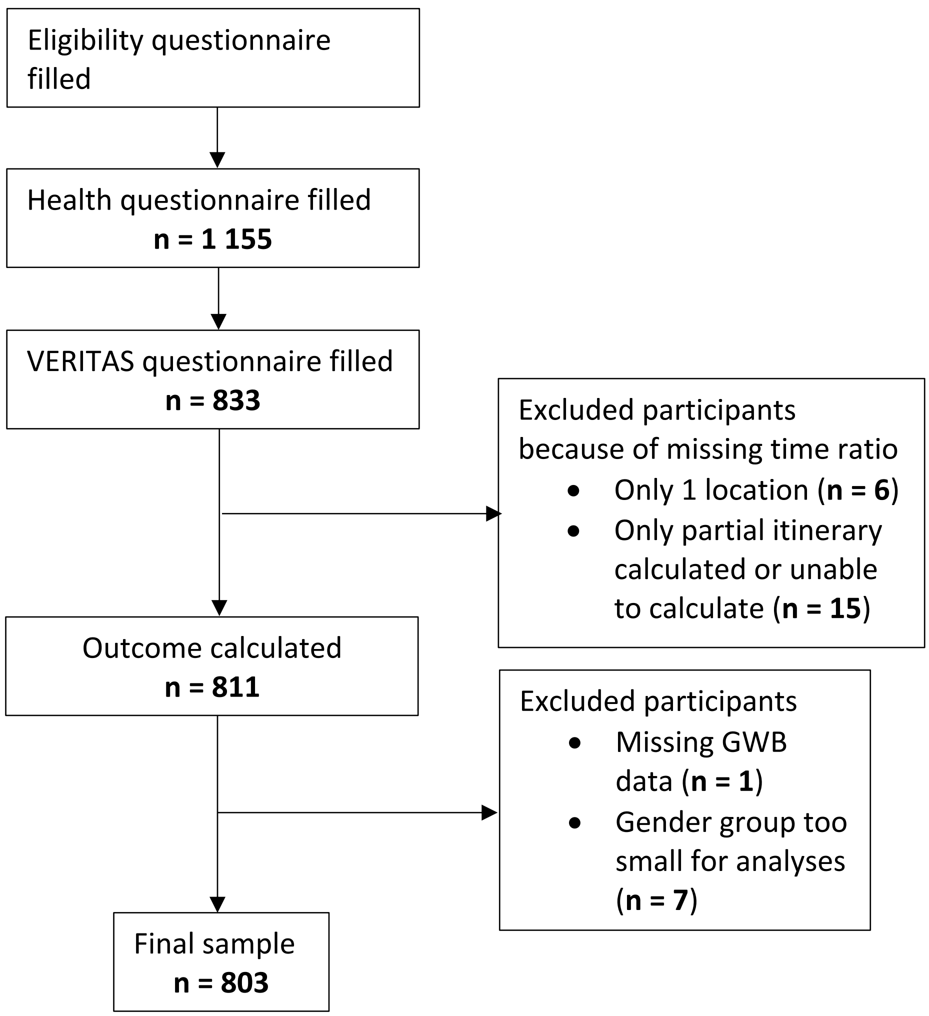

***Figure 8** : Attrition flowchart*

1 536 participants answered the eligibility questionnaire for the INTERACT Montréal's first cycle. Of those, 1 115 answered the health questionnaire and 833 answered the VERITAS questionnaire. Only those with complete answers to the VERITAS questionnaire were included in this study. The main outcome was calculated for 811 of those complete cases, with 22 participants for whom the ratio couldn't be calculated. 6 participants reported only one location of interest – thus rendering the calculation for trip time impossible. There was missing or partial itinerary information retrieved from Google, which prevented the calculation of the time ratio, for 15 participants. Additionally, one participant was excluded because of inconsistent data in their well-being scores. 7 participants were excluded because they identified to another gender identity than man/woman (including trans man and woman), creating groups with numbers too low to be included in the statistical models. The final sample had a total of 803 participants – although one participant was excluded from regression models due to an outlier transit fit measure value of 39.

	Non-user (N=94)	Low (N=381)	Medium (N=153)	High (N=175)	Overall (N=803)
Age					
Mean (SD)	49.9 (13.1)	48.2 (15.5)	41.8 (15.6)	38.1 (12.6)	45.0 (15.3)
Median [Min, Max]	52.0 [21.0, 80.0]	48.0 [20.0, 85.0]	39.0 [18.0, 78.0]	36.0 [18.0, 74.0]	43.0 [18.0, 85.0]
Gender					
Man	28 (29.8%)	132 (34.6%)	43 (28.1%)	52 (29.7%)	255 (31.8%)
Woman	66 (70.2%)	249 (65.4%)	110 (71.9%)	123 (70.3%)	548 (68.2%)
Education level					
Non University-educated	30 (31.9%)	56 (14.7%)	25 (16.3%)	27 (15.4%)	138 (17.2%)
University-educated	64 (68.1%)	325 (85.3%)	128 (83.7%)	148 (84.6%)	665 (82.8%)
PCS-12 physical component score					
Mean (SD)	50.5 (8.94)	52.6 (8.08)	53.1 (7.55)	53.5 (7.18)	52.6 (7.93)
Median [Min, Max]	53.8 [22.3, 63.8]	55.1 [20.9, 65.8]	55.1 [19.2, 64.1]	55.5 [23.3, 66.9]	55.0 [19.2, 66.9]
Access to a car					
Yes	91 (96.8%)	339 (89.0%)	130 (85.0%)	135 (77.1%)	695 (86.6%)
No	3 (3.2%)	42 (11.0%)	23 (15.0%)	40 (22.9%)	108 (13.4%)
Car Ownership					
Yes	90 (95.7%)	268 (70.3%)	90 (58.8%)	85 (48.6%)	533 (66.4%)
No	4 (4.3%)	113 (29.7%)	63 (41.2%)	90 (51.4%)	270 (33.6%)

Table 2 *: Baseline characteristics of INTERACT participants who completed the VERITAS questionnaire and for whom the outcome was calculated (n = 803), by frequency of public transit use*

The mean age was 45.0 years with a SD of 15.3 (*median*: 43.0 years with a min at 18 years and max at 85 years). There were 255 men (31.8% of the sample), including trans men, and 548 women (68.2% of the sample). In terms of the education attainment, 665 participants reported having a university-level degree (82.8%) versus 138 who did not (17.2%). The mean PCS-12 physical component score was 52.6 with a SD of 7.93 (*median*: 19.2).

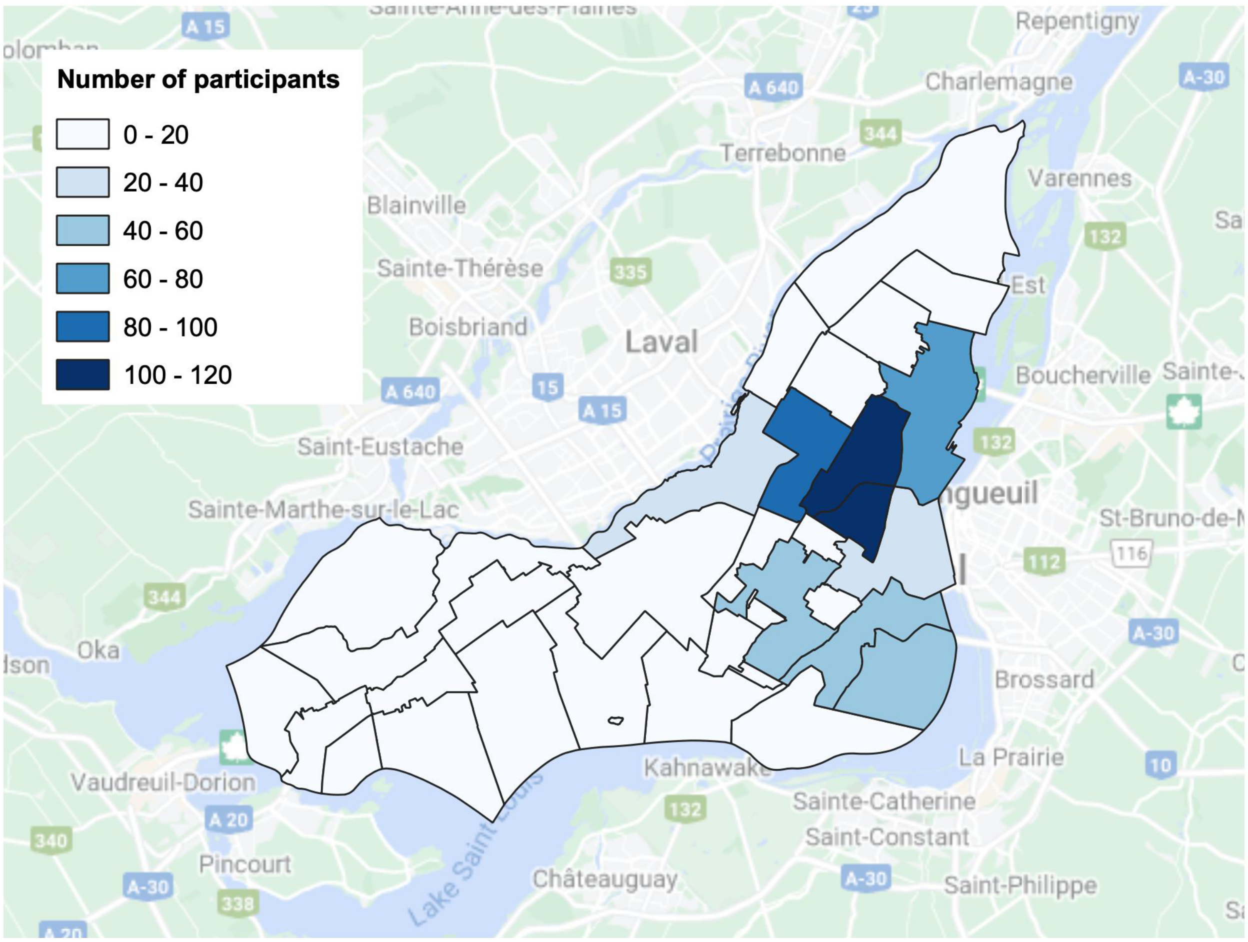

Figure 9 *: Number of participants included in the final sample, per neighbourhood or city on the Island of Montréal*

668 participants had a home address on the Island of Montréal (including linked cities not within the City of Montréal), 41 in the Laval region, and the remaining 94 participants lived on the South Shore of Montréal (Longueuil, St-Lambert, and Brossard). The most represented neighbourhoods in the sample were mostly central neighbourhoods, with Rosemont-La Petite-Patrie (110 participants), Le Plateau-Mont-Royal (98), Villeray-Saint-Michel-Parc-Extension (80),

Mercier- Hochelaga-Maisonneuve (61) and Le Sud-Ouest (57) representing almost half of the sample – for a map of Montréal's neighbourhoods, see Appendix IV.

Table 3 *:* Number of participants per neighbourhood in the city of Montréal (excluding those living in Laval or in the Longueuil, St-Lambert and Brossard agglomeration)

Arrondissement	Number of participants
Rosemont-Petite-Patrie	110
Le-Plateau-Mont-Royal	98
Villeray-St-Michel-Parc-Extension	80
Mercier-Hochelaga-Maisonneuve	61
Le Sud-Ouest	57
Côte-des-Neiges/Notre-Dame-de-Grâce	52
Verdun	43
Ville-Marie	35
Ahuntsic-Cartierville	34
Rivières-des-Prairies-Pointe-aux-Trembles	13
Saint-Laurent	12
LaSalle	11
Montréal-Nord	10

Descriptive statistics

Geographic accessibility to public transit

Geographic accessibility – that is walking access to public transit – was explored as both a continuous and as a categorical variable, following the methods outlined in the previous chapter (Chapter 3). The thresholds were based on the 85th percentile of acceptable walking distance according to participants in a Montréal study by El-Geinedy et al (2014), greater for the nearest metro station (873.35 m) and nearest train station (1259.41 m). Only 60 participants do not live in areas where bus stops are reputed to be within acceptable walking distance.

*__Table 4__ : Number of participants according to transit mode and distance of nearest stop from residential address**

Distance	Bus	Metro	Rail
100 m	204	7	0
200 m	322	9	0
400 m	217	60	2
600 m	-	64	11
800 m	-	76	11
1 000 m	-	84	20
1 250 m	-	-	32
Non-accessible**	60	503	727

**N.B.: for bus stop distance, the distance threshold for accessibility was reduced to 400 m in accordance with previously cited literature.*

*** Thresholds chosen (beyond 400 m for bus, beyond 1 000 m for metro, and beyond 1 250 m for rail) correspond to the 85th percentile of acceptable walking distance according to participants in a Montréal study by El-Geinedy et al (2014).*

Public transit use in the sample population

Most participants were public transit users in 2018 (709 participants, or 88.2%). Only a small minority reported not using any public transit at the time of the INTERACT data collection. However, as seen on Figure 10, most users – 47.4% – reported low frequency of use (i.e., ≤ 1 day/week or 1-51 days/year), compared to a medium or high frequency of use: 19.1% reported using public transit for 1-4 days/week and 21.7% for ≥ 5 days/week. The mean transit use frequency was 136 days per year for the whole sample (*median*: 117 days per year). It is interesting to analyse the proportion of car owners within each of these categories, which we can also visualise on Figure 10. Indeed, the proportion of car owners is very high in those who do not use public transit and gradually decrease with increasing public transit use. Overall, 270 participants (33.5%) reported not owning a car, but less than half of those (108) reported to not have access to a car at all.

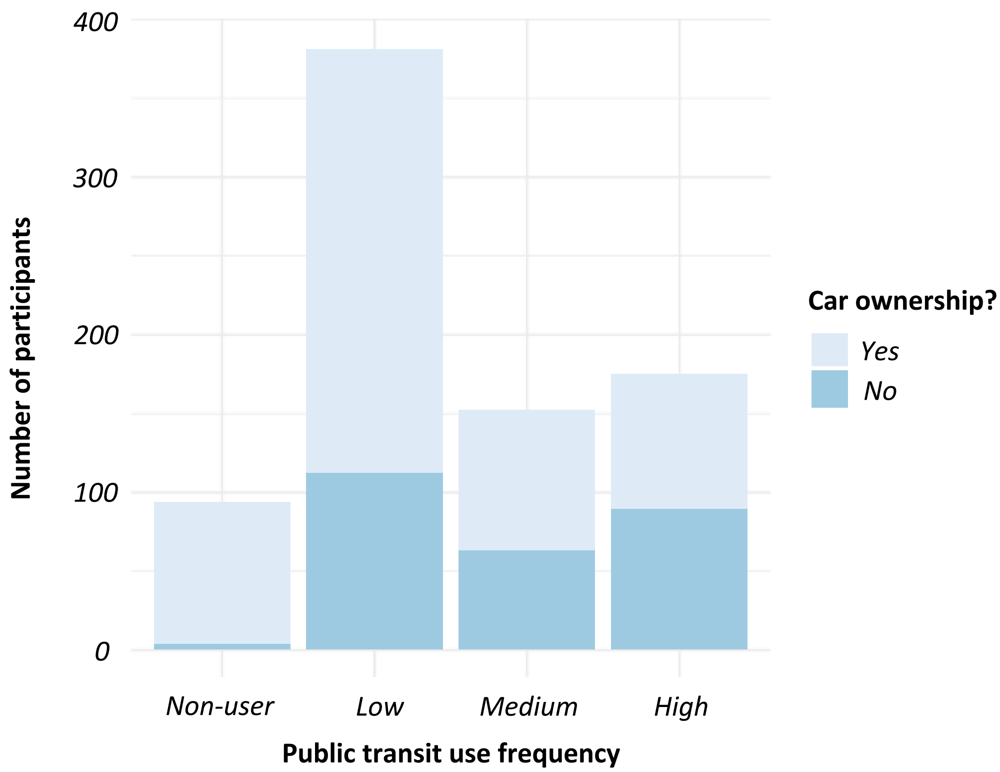

Figure 10 *: Stacked bar graph of number of participants who are car owners themselves or not in each public transit use frequency category*

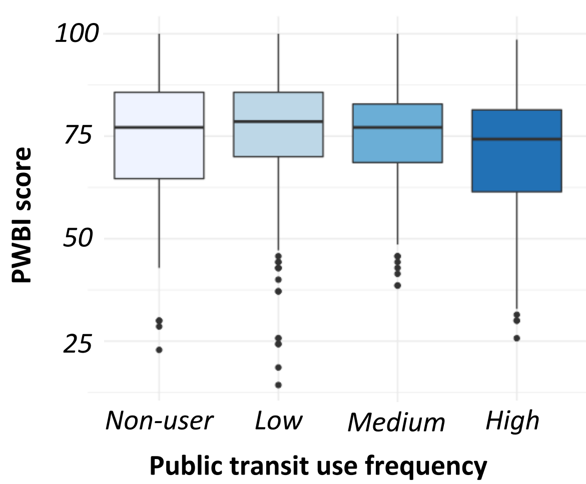

Figure 12 *: Boxplot of PWBI score by public transit use frequency category*

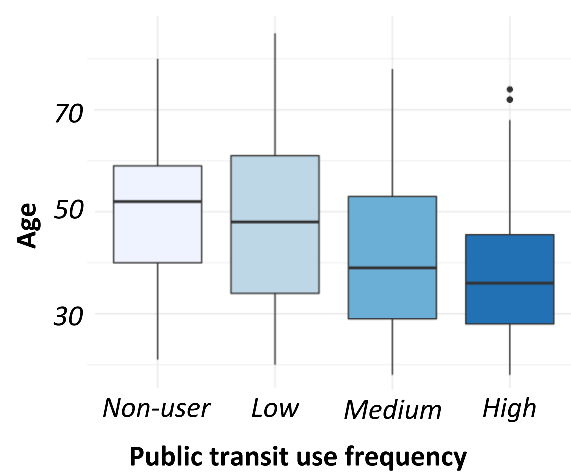

Figure 11 *: Boxplot of age by public transit use frequency category*

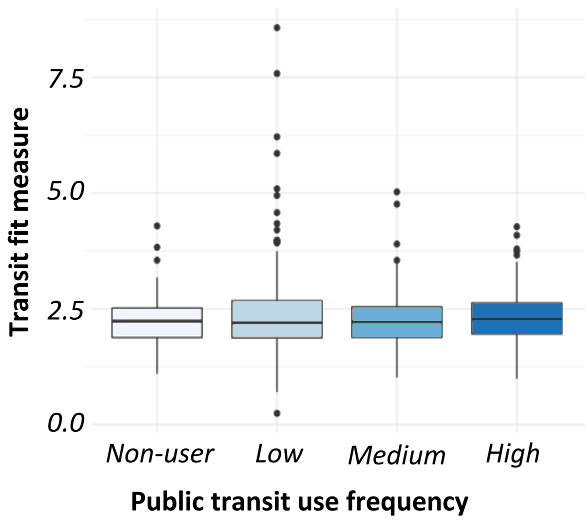

Figure 13 : *Boxplot of transit fit measure spread by public transit use frequency*

According to the boxplot shown in Figure 12, the mean PWBI score does not significantly vary depending on public transit use frequency. Participants in the high public transit usage group were on average younger than those in the other groups (see Figure 11). In terms of correlation with the transit fit measure calculated previously (see Chapter 4 for a more comprehensive look at descriptive statistics), we can see on Figure 13 that it does not seem to be associated with public transit use frequency as its median value is relatively stable within all categories. Of note, access to public transit was a desired neighbourhood feature for most respondents and factors in their residential choice: 733 participants rated the fact that their neighbourhood had good access to public transit as "very important" (*n* = 591) or "somewhat important" (*n* = 142).

Multiple linear regression models

A simple linear regression model showed that there was an average increase of 0.90 point in the PWBI score per increment of 1 in the transit fit measure (β *= 0.90 with 95% CI [-0.56, 2.36])* (Table 5, Univariate model 1), which is not statistically significant at a significance level of 95%. Similarly, a multiple linear regression model adjusting for yearly transit use, car ownership, age, gender, education, and physical health showed similar results (β *= 0.99 with 95% CI [-0.40, 2.38])* (Table 5, Multivariate model 2).

Age was positively associated with the PWBI score, with an average increase of 0.15 point in the PWBI score (β *= 0.15 with 95% CI [0.08, 0.22]*) (Table 5, Multivariate model 2) per 1 year of age gained compared to the average age of the sample, all other variables remaining equal.

Reporting good physical health was also associated with increased PWBI score when controlling for all other covariates: there was an average increase of 0.50 point (β *= 0.50 with 95% CI [0.37, 0.63]*) (Table 5, Multivariate model 2) for each increase of 1 point in the score of the physical component of the SF-12, holding other variables constant. Participants with a university degree had a significantly higher PWBI score (on average, 3.97 points higher) than those without a university degree (β *= 3.97 with 95% CI [1.37, 5.58]*) (Table 5, Multivariate model 2).

Low and medium public transit use were not associated with the PWBI score. However, although it failed to reach statistical significance, high public transit use (≥ 5 times/week) was associated with an average decrease of 3.46 points in the PWBI score (β *= -3.46 with 95% CI [-7.19, 0.27])* (Table 5, Multivariate model 2) when compared to a person not using public transit at all, all other variables being held constant. A similar observation can be made for car ownership, which seems to be positively correlated with the PWBI score without being statistically significant: on average, car owners had a 2.01 points higher PWBI score than those who did not own a car (β *= 2.01 with 95% CI [-0.13, 4.15]*) (Table 5, Multivariate model 2).

All other covariates were not statistically significant at a 95% significance level. The model using all covariates (Table 5, Multivariate model 2) had an adjusted R^2 of 0.1075, meaning that this model only explained 10.75% of the variance of the outcome variable.

Table 5 *: Regression coefficients and 95% confidence intervals for main multiple linear regression models, with PWBI score as a dependent variable*

Dependent variable PWBI score	**Univariate model** n = 802 Coefficient β [95%CI]	**Multivariate model 1** n = 802 Coefficient β [95%CI]	**Multivariate model 2** n = 802 Coefficient β [95%CI]	**Multivariate model 3** n = 802 Coefficient β [95%CI]
Constant	**72.57*** [69.01, 76.13]	**70.69*** [65.88, 75.49]	**41.02*** [32.63, 49.41]	**43.30*** [35.54, 51.06]
Transit fit measure	0.90 [-0.56, 2.36]	0.77 [-0.68, 2.22]	0.99 [-0.40, 2.38]	

Low transit use ƚ		2.63 [-0.71, 5.97]	1.16 [-2.07, 4.40]	1.33 [-1.90, 4.55]
Medium transit ƚ use		1.46 [-2.37, 5.39]	0.75 [-2.97, 4.47]	0.83 [-2.89, 4.55]
High transit use ƚ		-3.07 [-6.87, 0.73]	-3.46 [-7.19, 0.27]	-3.31 [-7.04, 0.41]
Car ownership		2.02 [-0.21, 4.26]	2.01 [-0.13, 4.15]	0.15 [-0.06, 4.23]
Age (centered to the mean)			**0.15*** [0.08, 0.22]	**0.80*** [0.08, 0.22]
Woman			0.75 [-1.34, 2.84]	3.89 [-1.30, 2.89]
University-level education			**3.97*** [1.37, 5.58]	**2.01*** [1.29, 6.49]
*Reported physical health***			**0.50*** [0.37, 0.63]	**0.50*** [0.37, 0.63]
R^2 (adjusted R^2)	*0.0018 (0.0005)*	*0.0320 (0.0259)*	*0.1176 (0.1075)*	*0.1154 (0.1065)*

** Green cells show variables that are statistically significant ($p < 0.05$), whereas yellow cells show those that are not but show a clear tendency towards a positive of a negative correlation*
*** Physical component score of SF-12*
ƚ Low transit use = < 1 day/week, or 1-51 days/year
Medium transit use = 1-4 days/week, or 52-259 days/year
High transit use = ≥ days/week, or ≥ 260 days/year

Sensitivity analyses

Pre-specified multiple linear regression models (sensitivity analyses) were done replacing the main predictor, the transit fit measure (a continuous variable), with the following variables to assess how certain analytical decisions made influenced the outcomes of this study:

- Transit fit measure recategorized as a binary variable: ratio of transit and car travel times computed between participants' home and workplace, calculated as discussed in Chapter 4 (threshold at 3.03 i.e., mean + 1 SD);

- Transit fit measure recalculated using only home-work journeys; and
- Annual frequency of use of public transport as a continuous variable, instead of a categorical value.

Covariates that were statistically significant in the main multiple linear regression model (Table 5, Multivariate model 2) remain mostly significant in all alternate models, except for age when exchanging the original transit fit measure for an alternate version accounting only for home-work commuting trips (β *= 0.04 with 95% CI [-0.06, 0.14]*). This may be due to a lack of statistical power resulting from a lower n than other models shown, or that the non-working population may have different transit habits or a different subjective understanding of well-being. Moreover, without being statistically significant, there is a signal that this alternate version of the measure may yield an average increase of 0.82 points in PWBI score (β *= 0.82 with 95% CI [-0.12, 1.77])* per increase of 1 unit in the transit fit measure, all other variables being equal (Table 6, Alternate model 2).

Owning a car yields a statistically significant increase in PWBI score compared to not owning a car, when the public transit use variable is continuous instead of categorical (β *= 2.59 with 95% CI [0.51, 4.66]*) (Table 6, Alternate model 3). Car ownership is not statistically significant for the alternate model 2, although this may be due, again, to a lack of statistical power because of the lower *n* (Table 6, Alternate model 2).

In both models where alternative transit fit measures are used, there remains a signal that high public transit use may be correlated with a decrease in PWBI score even though the regression coefficient is not significant per se. All other covariates (except age as previously discussed) were not statistically significant at a 95% significance level. The models used for these sensitivity analyses had an adjusted R^2 ranging between 0.0650 to 0.1053, meaning that this model only explained 6.50 to 10.53% of the variance of the outcome.

***Table 6** : Regression coefficients and 95% confidence intervals for multiple linear regression models with <u>alternate transit fit measure and transit use calculations</u>, with PWBI score as a dependent variable*

<u>Dependent variable</u> PWBI score	**Alternate model 1** n = 802 Coefficient β [95%CI]	**Alternate model 2** n = 587 Coefficient β [95%CI]	**Alternate model 3** n = 802 Coefficient β [95%CI]
Constant	**43.29*** [33.59, 52.99]	**45.75*** [35.93, 55.56]	**40.27*** [32.11, 48.43]
Transit fit measure			0.10 [-0.40, 2.39]
Transit fit measure (categorical version)	0.01 [-6.22, 6.25]		
Transit fit measure (only home-work trips)		0.82 [-0.12, 1.77]	
Low transit use ł	1.33 [-1.91, 4.56]	0.31 [-3.69, 4.32]	
Medium transit ł use	0.83 [-2.89, 4.56]	0.13 [-4.31, 4.56]	
High transit use ł	-3.31 [-7.05, 0.42]	-3.74 [-8.07, 0.59]	
Annual transit use frequency			0.00 [-0.01, 0.01]
Car ownership	2.90 [-0.06, 4.23]	0.78 [-1.72, 3.28]	**2.59*** [0.51, 4.66]
Age (centered to the mean)	**0.15*** [0.08, 0.22]	0.04 [-0.06, 0.14]	**0.18*** [0.11, 0.24]
Woman	0.80 [-1.30, 2.89]	1.12 [-1.37, 3.62]	0.64 [-1.47, 2.75]
University-level education	**3.89*** [1.28, 6.50]	**4.07*** [0.85, 7.29]	**4.10*** [1.50, 4.66]
*Reported physical health***	**0.50*** [0.37, 0.63]	**0.42*** [0.27, 0.58]	**0.50*** [0.38, 0.63]
R^2 (adjusted R^2)	*0.1154 (0.1053)*	*0.0794 (0.0650)*	*0.1033 (0.0954)*

** Statistically significant ($p < 0.05$) – green cells show variables that are statistically significant, whereas yellow cells show those that are not but show a clear tendency towards a positive or a negative correlation*
*** Physical component score of SF-12*
ł Low transit use = < 1 day/week, or 1-51 days/year
Medium transit use = 1-4 days/week, or 52-259 days/year
High transit use = ≥ days/week, or ≥ 260 days/year

As the transit fit measure is a novel metric developed in the context of this thesis, it is also interesting to assess the use of alternative "traditional" accessibility measures (i.e., number of public transit stops within 1km, as well as distance to nearest bus, metro and train stop for each individual) as the main outcome for sensitivity analyses. The conclusions are identical to those stemming from the main model. The models used for these sensitivity analyses had an adjusted R^2 ranging between 0.1053 to 0.1078, which is also in line with the main model (Table 7, Alternate model 4-7).

***Table 7** : Multiple linear regression models with alternate accessibility metrics as exposure variables, with PWBI score as a dependent variable*

Dependent variable PWBI score	**Alternate model 4** n = 802 Coefficient β [95%CI]	**Alternate model 5** n = 802 Coefficient β [95%CI]	**Alternate model 6** n = 802 Coefficient β [95%CI]	**Alternate model 7** n = 802 Coefficient β [95%CI]
Constant	**44.64*** [36.68, 52.60]	**44.50*** [34.65, 50.31]	**43.26*** [35.44, 51.08]	**44.14*** [36.26, 52.01]
Number of public transit stops within 1 km	-0.03 [-0.07, 0.01]			
Distance to nearest bus		0.01 [-0.00, 0.01]		
Distance to nearest metro			0.00 [-0.00, 0.00]	
Distance to nearest train				-0.00 [-0.00, 0.00]

Low transit use ꝉ	1.47 [-1.76, 4.70]	1.30 [-1.92, 4.53]	1.33 [-1.90, 4.56]	1.39 [-1.84, 4.62]
Medium transit ꝉ use	0.94 [-2.78, 4.66]	0.80 [-2.91, 4.52]	0.84 [-2.89, 4.60]	0.88 [-2.84, 4.60]
High transit use ꝉ	-3.18 [-6.91, 0.55]	-3.32 [-7.04, 0.41]	-3.32 [-7.05, 0.416]	-3.31 [-7.04, 0.42]
Car ownership	2.05 [-0.09, 4.19]	2.02 [-0.12, 4.16]	2.10 [-0.06, 4.23]	2.04 [-0.10, 4.19]
Age (centered to the mean)	**0.15*** [0.07, 0.22]	**0.15*** [0.08, 0.22]	**0.15*** [0.08, 0.22]	**0.15*** [0.08, 0.22]
Woman	0.87 [-1.22, 2.97]	0.73 [-1.36, 2.83]	0.80 [-1.30, 2.89]	0.82 [-1.28, 2.91]
University-level education	**3.86*** [1.26, 6.46]	**3.92*** [1.32, 6.52]	**3.89*** [1.29, 6.49]	**3.91*** [1.31, 6.51]
*Reported physical health***	**0.50*** [0.37, 0.63]	**0.49*** [0.37, 0.62]	**0.50*** [0.37, 0.63]	**0.50*** [0.37, 0.63]
R^2 (adjusted R^2)	*0.1178* *(0.1078)*	*0.1179* *(0.1078)*	*0.1154* *(0.1053)*	*0.1170* *(0.1070)*

** Green cells show variables that are statistically significant, whereas yellow cells show those that are not but show a clear tendency towards a positive or a negative correlation*

*** Physical component score of SF-12*

ꝉ Low transit use = < 1 day/week, or 1-51 days/year
Medium transit use = 1-4 days/week, or 52-259 days/year
High transit use = ≥ days/week, or ≥ 260 days/year

Chapter 6: Discussion

This chapter will discuss this study's results and substantive contributions within the context of current evidence regarding the association between accessibility to public transit and SWB, as well as highlight novel approaches that were used to analyse the data. Strengths and limitations of the study design will be discussed. An overview of potential policy implications and next research avenues will complete this section.

Substantive contributions

The main objective of this study was to determine if public transit accessibility to key destinations is associated with increased wellbeing, controlling for public transit use frequency and other covariates. Accessibility is a complex construct that is difficult to measure accurately, one way being to assess the time to travel between an origin and a destination. This depends on transportation mode, but also external factors such as the development of road and/or transit infrastructure, construction operations, traffic, etc. Our idea of transit accessibility is based the ratio of time it takes to reach a destination when using transit versus a car. It is in this context that we created a measure of individual transit fit using that time ratio, using open-access data from Google Maps, which was compared to other described metrics in the literature.

The transit fit measure - i.e., the ratio of time spent in public transport vs in car for a set of possible trips for a given individual - does not seem to have a significant association with well-being, when all other covariates are included in the model. This measure is in its first iteration and would require further refinements and development, as well as more precise input data to accurately reflect daily trips undertaken by the participant. As we recall, some evidence shows that longer commute times are associated with decreases in LS (Ingenfeld et al., 2019) and health satisfaction (Künn-Nelen, 2016). This relationship seems to be mediated by satisfaction with leisure time (Ingenfeld et al., 2019). Sensitivity analyses were performed replacing the transit fit measure by "traditional" accessibility measures (i.e., number of public transit stops within 1 km, as well as distance to nearest bus, metro, and train stop for each individual), with no appreciable changes in our conclusions. There seems to be a signal that high public transport use (i.e., ≥ 5 times/week or ≥ 260 times/year) contributes to a decrease in LS.

As expected from past research, education, age, and physical health were associated with LS (PWBI score) in our sample. *Education* seemed to have the strongest positive association with LS out of the three statistically significant predictors with, on average, a 3.97-point increase in PWBI score for participants holding a university degree versus those who don't. This fits with evidence that education level has direct and indirect effects on LS through its association with health status and income (Pinquart & Sörensen, 2000; Dolan et al., 2008). Consistent with previously stated evidence that *age* was associated with a decrease in reported LS scores from teenage years through midlife (Fortin et al., 2015; Steptoe et al., 2014), our study shows a small but statistically significant increase of 0.15 point on the PWBI score per year beyond the mean age in the sample (45 years old). However, this finding would fit with the U-shaped recovery in LS scores observed after age 40-50. As the age variable was centered to the mean in our regression models, and the overall age distribution of the sample was skewed to the right, this positive association between age and LS is therefore expected. Our study also shows a small, statistically significant positive association with *reported physical health*, which is in line with previous findings (Diener & Seligman, 2004).

There was no significant observed relationship between *gender* and LS in our study, contrary to evidence collected from the Gallup World data (Fortin et al., 2015). However, studies showing positive associations between gender and LS have shown only a small increase in scores and have been done on samples with thousands of participants: it may very well be that our study did not have sufficient power to capture this association.

As highlighted in the literature review in Chapter 2, well-being is a complex, multi-factorial variable of interest that depends both on external and internal factors affecting the individual. Therefore, it is highly likely that the well-being indicator used in this study is influenced by unmeasured confounders that we were unable to include in the multiple linear regression models that were built. This is in concordance with previously discussed evidence that external factors could have as low as a 10% contribution to measured SWB (Lyubomirsky et al., 2005).

Study strengths and limits

This study is, to our knowledge, the first to assess the association between public transit accessibility to key locations compared to car accessibility (the transit fit measure) and well-being indicators. In this study, accessibility mostly focused on the time it takes to reach a location of interest. The thorough questionnaires filled by the INTERACT cohort participants, especially the VERITAS questionnaire, provided accurate and detailed data about locations of interest visited by participants and frequency of visits.

Some sources of bias exist within this study, starting with a selection bias which may stem from the recruitment methods used for the INTERACT study, as well as increased interest in public transit studies by current active users. Only adults aged 18 and older were eligible to participate in the survey, even though youth – particularly high school students and college-aged young adults – are a significant user base according to the ARTM O-D survey published in 2016 (Autorité régionale de transport métropolitain, 2020). As shown by the descriptive statistics, the sample is not representative of the CMM population: there is a significantly higher proportion of university-educated participants (82.8% vs 33% of 25–64-year-old in the CMM in 2016) and women (68.2%) (Observatoire de la Communauté métropolitaine de Montréal, 2021). We can also see an over-representation of central Montréal neighborhoods, that tends to be well-connected to public transit and overall present built environment characteristics that promote use of public transit or active transportation. Further analyses could be done to assess if transit use influences the association between the transit fit measure and PWBI score (interaction between the two variables).

Moreover, as this is a cross-sectional study, there was no possibility of studying changes in public transit accessibility over time and its effects on well-being. This will however be possible in 2022 with the 2nd wave of data collection completed in Montréal.

In addition, as discussed previously, no data on ethnicity/race was available. Also, the low number of respondents who declared a gender identity other than cis-man or cis-women hindered the statistical analysis of collected data for this group. This posed a methodological problem when it came to statistical analysis, which unfortunately lead to removing those participants from the sample which affected representativity. Evidence shows that queer visibility and the subsequence fear of harassment and perception of lack of safety greatly affect queer people in their travel behaviours (Weintrob, 2018). Further attention should be given to this issue, as current INTERACT data analysed in this study may not specifically reflect specific barriers to public transit access that these groups potentially experience while travelling within the CMM territory.

Contribution to the field

This thesis brought to the table a novel public transit accessibility measurement methodology assessing the ratio of travel time by public transit versus by car for daily trips for a single individual, using open-access data from Google to circumvent the requirement for labour-intensive specialized GIS procedures. The innovative aspect of this measure lies in the use of real destinations provided by the participants via the VERITAS questionnaire, which could be further enhanced by recording origin locations for each destination for more accurate analysis. The individual's residence is at the center of the measure and not general accessibility of a specific location from all possible starting points, unlike other accessibility measures commonly used. Although this method will most likely require some fine-tuning, this is to our knowledge the first individual measure to do so using high-fidelity location data and open-access data.

Policy implications

Well-being is a construct influenced by multiple factors, both quantifiable (age, education, income, etc.) and non-quantifiable (personality traits, life experience, social network, etc.) Therefore, it may be difficult to capture associations with several confounding variables – known and unknown. Similarly, as discussed throughout this thesis, accessibility is a broad concept that not only refers to traditional quantitative objective metrics, but also should consider one's resources and abilities, as well as their needs to paint a more complete portrait of the situation. Current imperfect accessibility measures may not adequately reflect the complexity of the concept.

The quality and availability of public transit options directly affect their use (Bailey, Mokhtarian, & Little, 2008). It is interesting that most participants had a transit fit measure higher than 1, meaning that public transit is more time-consuming than driving a car for daily trips for these individuals. Notwithstanding parking fees and time, which may skew the mode used in certain situations, this highlights the fact that public transit may not be the most competitive option for daily trips for a majority of Montrealers. Despite this, there was no significant association between the value of the transit fit measure and transit use in our sample, even when accounting for factors that may influence public transit uptake such as socioeconomic characteristics and residential selection. Public transit can sometimes be perceived as less efficient, because of low service frequencies, wait times and transfers, and commuter satisfaction decreases (Lunke, 2020; Higgins, Sweet, & Kanaroglou, 2017). Some may be content to use public transit despite these inefficiencies because of personal factors or other secondary benefits (increased physical activity, decreased cost, free time for other tasks, personal convictions, etc.) (Litman, 2021). For others, this may lead them to choosing their car instead of public transit, even when the service is available. It is this category of people – car users who would use public transit if it were a more competitive and enjoyable option that is aligned with their needs – that should be targeted by interventions that lead to mode switching, such as subsidizing transit passes (Schubert, Henning, & Becker Lopes, 2020; Abou-Zaid & Ben-Akiva, 2012), reducing transfers and crowding (Idris, Habib, & Shalaby, 2014), and expanded coverage. (Litman, 2021, p. 13) To go further, the transit fit measure and other similar metrics, when combined with population density measures, could be used to guide sustainable transit development by identifying areas where the car may be the most competitive transportation mode available and where investments (to increase service frequency, develop new transit access points, etc.) would be most efficient to increase public transit ridership.

Discussion about public transit in 2022 cannot overlook the impact of the COVID-19 pandemic on public transit use. Reduction in demand stemmed from both decreased mobility due to wide-range public health restrictions on work activity (including shelter-in-place orders and curfews), as well as users' fear of contracting COVID-19 through contact with potentially infectious travellers within the public transit system (Liu et al., 2020). This is not unique to COVID-19: data from the 2003 SARS pandemic in Taipei, Taiwan and the 2015 SARS outbreak in Seoul, South Korea, show also declines in ridership (Wang, 2014; Kim et al., 2017). Increasing users' satisfaction and trust in transit systems post-pandemic will be an essential component in the ongoing efforts of transit agencies to promote sustainable transportation and a decrease in our reliance on cars for daily activities. With COVID-19 leading to repeated lockdowns in 2020 and 2021, the concept of "15-min cities" – or neighbourhoods where people can live, work, and buy essentials by walk or bike within a 15-min radius – has become more popular as the importance of proximity services is underlined time and time again (Moreno et al., 2021). However, implementing this idea of the 'multicentric city' requires efficient, convenient, and affordable public transit options that people will trust and want to use to render it truly sustainable.

Although it may be utopian to aim to optimize public transit systems for all possible outcomes, it seems imperative that policymakers involved in transportation planning should integrate well-being indicators (including customer satisfaction metrics) into quality improvement processes, especially in the perspective of Transit Oriented Development and sustainable development targets (Delbosc, 2012; Transit Cooperative Research Program, 2004). Beyond simply adding to monitored metrics, transportation officers and other stakeholders should also consider how efficient and accessible public transit can help attain other desired societal goals, such as reduction in unemployment or reduction in greenhouse gas emissions.

Chapter 7: Conclusion

This cross-sectional study aimed to examine the association between public transit accessibility and indicators of subjective well-being in the population of the Montréal Metropolitan Region. A measure aiming to compare the ratio of time spent in public transport vs in car for a set of possible trips for a given individual was developed using detailed itinerary data from INTERACT and open-access data from Google Maps, without recourse to labour-intensive GIS methods. This was proposed to overcome issues previously described with traditional methods.

The transit fit measure developed over the course of this study did not seem to be associated with well-being. Other sensitivity analyses were done replacing the main predictor by traditional accessibility measures, without any significant changes to the conclusions drawn from the main multiple linear regression models. As expected from the literature, age, education, and physical health were associated with subjective well-being in our sample. Although this was not statistically significant, high public transport use (i.e., ≥ 5 times/week or ≥ 260 times/year) seems to contribute to a decrease in well-being in our sample, whereas car ownership seems to increase it. Despite some inconclusive outcomes, this thesis contributes to the growing evidence base exploring the association between public transit and well-being in the public health and urban planning fields.

In the light of the study's results, it is evident that this version of the transit fit measure could benefit from incorporating qualitative data regarding the trips taken by the INTERACT participant groups. Indeed, it would be interesting to explore the definition of public transit accessibility and factors influencing accessibility, trip enjoyment and life satisfaction for INTERACT participants in general. This could in turn inform the relationship between public transit accessibility and its use, potentially uncovering interactions that may not be readily visible in quantitative data. Another future research avenue could be to study the possible causal path between the availability of public transport and increased social participation for certain groups of the population (older adults, youth and children, low-income populations, gender identity, etc.)

Transportation planning is a complex endeavour, both because of the multitude of different inputs that need to be considered, and because of human needs that are constantly evolving through time, space, and social norms. However, as described throughout this thesis and in the growing literature about this subject, public transit can have an impact on individuals' subjective well-being through multiple pathways including, but not restricted to, mood related to trip satisfaction, perception of public transit, and access to essential resources like health services, employment, and nutritious foods. The plurality of those possible levers of action underlines the need for an integrated, intersectoral strategy to enable our population to reach – quite literally – their full potential.

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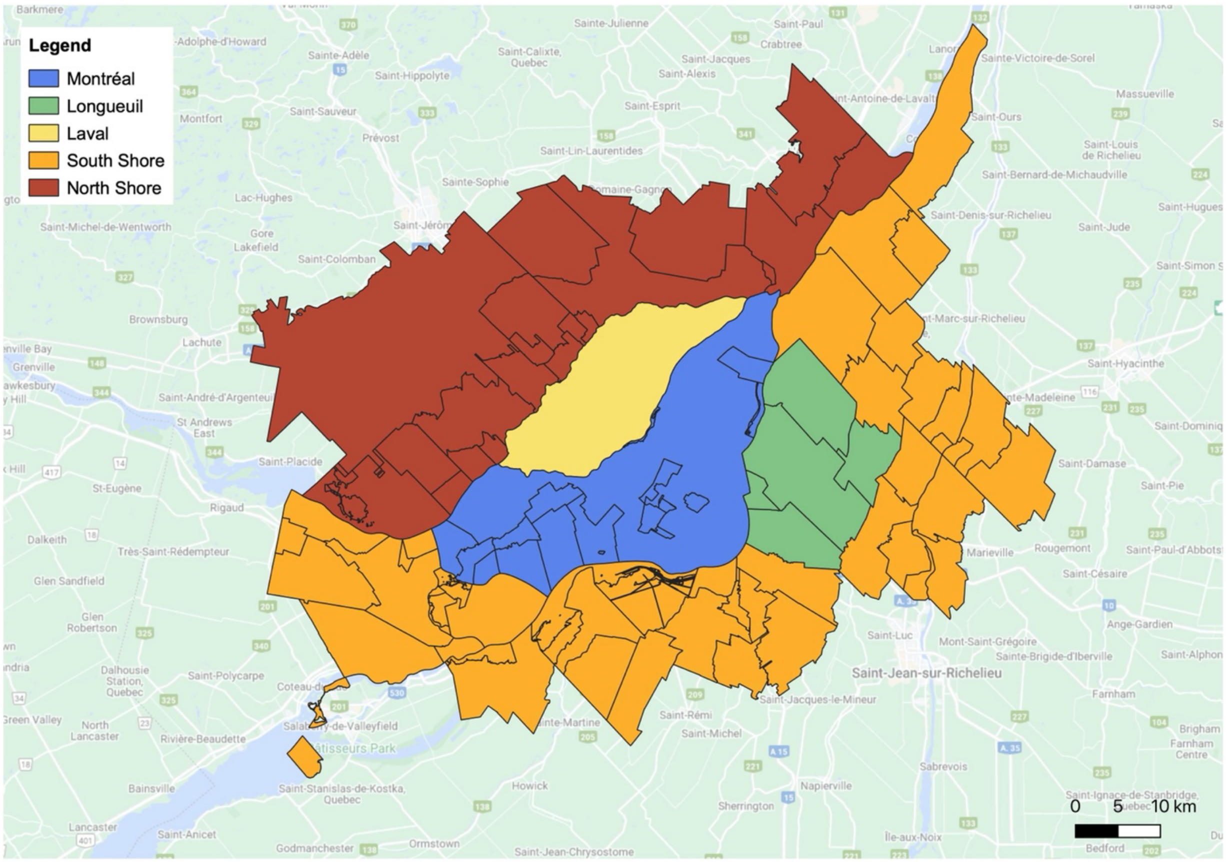
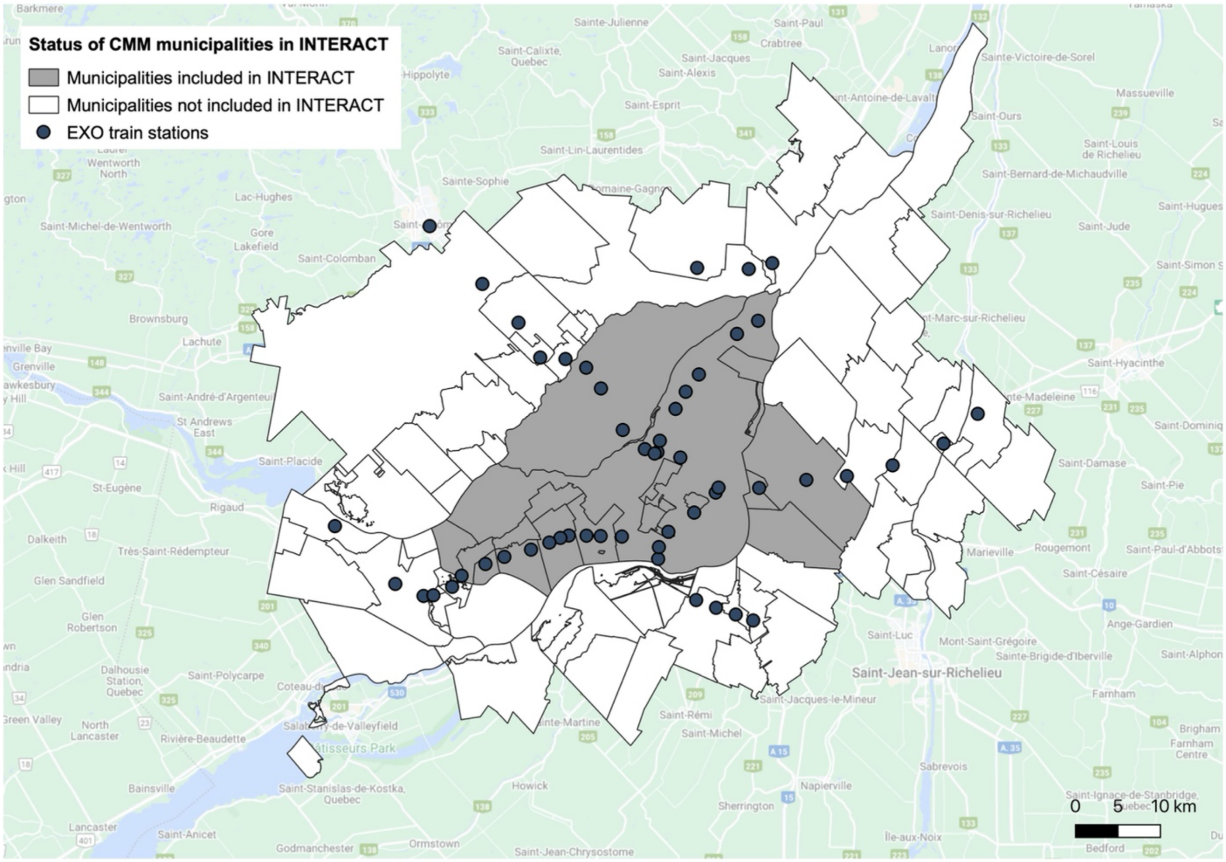
Appendix I: Map of the CMM



SOURCE: Zaïm, C. (2022) *Map of the CMM* [map]. Scale 1: 700 000. Data layers: Google Maps layer within QGIS; Municipal boundaries (AQcarto) [computer files]. Montréal, QC: McGill University. Generated on June 15th, 2022. Using QGIS Geographic Information System [GIS software]. Version 3.22 (2022). QGIS Association.

Appendix II: Status of CMM municipality in INTERACT

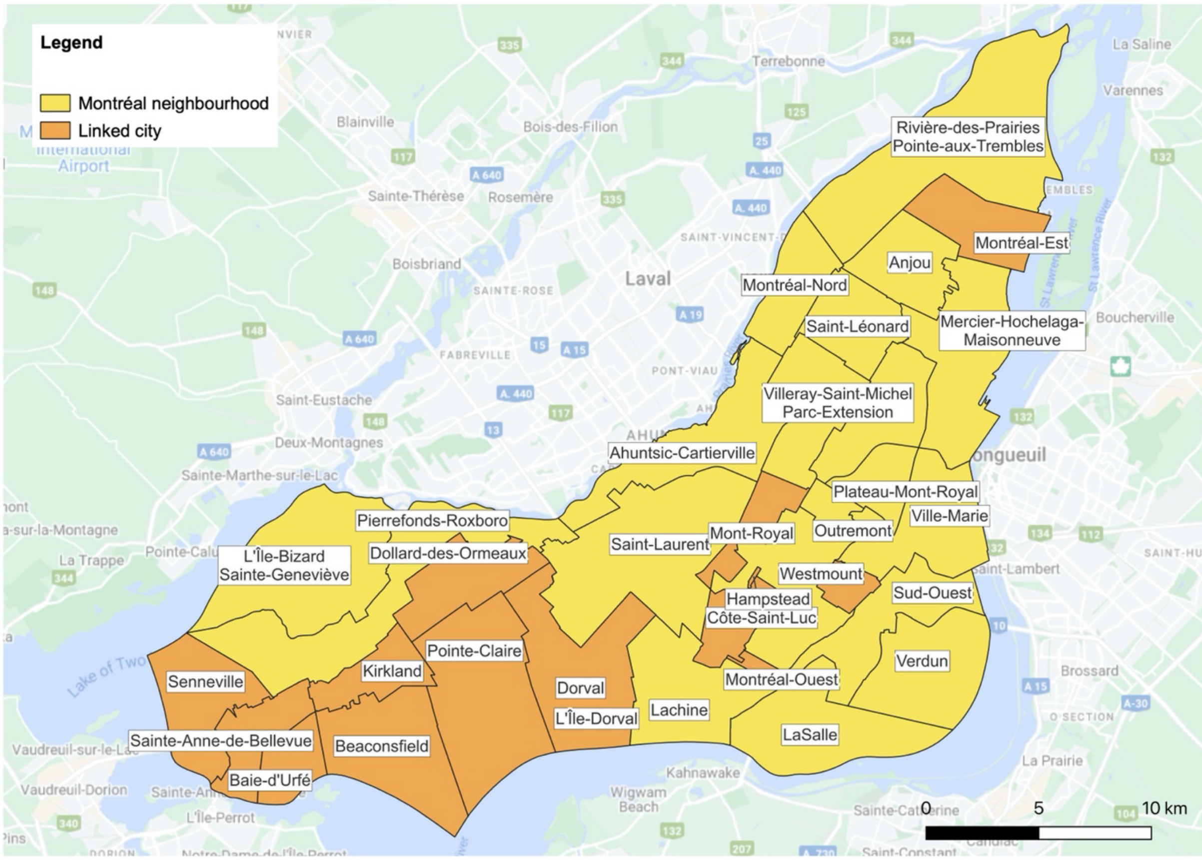


SOURCE: Zaïm, C. (2022) *Status of CMM municipality in INTERACT* [map]. Scale 1:700 000. Data layers: Google Maps layer within QGIS; Municipal boundaries (AQcarto); Données GTFS Trains – exo1, exo2, exo3, exo4, exo5 et exo6 [computer files]. Montréal, QC: McGill University. Generated on June 15th, 2022. Using QGIS Geographic Information System [GIS software]. Version 3.22 (2022). QGIS Association.

Appendix III: List of all locations of interest included in INTERACT's VERITAS questionnaire

Locations
bakery
bank
convenience store
cultural leisure
doctor or HCP
drugstore
hair salon
home
leisure physical
liquor store
other locations
other residence
park
post office
public market
public transit
religious
restaurant take-out
restaurant/food est.
school
specialty food store
supermarket
volunteering
walk
work

Appendix IV: Map of Montréal's boroughs



SOURCE: Zaïm, C. (2022) *Map of Montréal's boroughs* [map]. Scale 1: 265 000. Data layers: Google Maps layer within QGIS; Limites administrative de l'agglomération de Montréal [computer files]. Montréal, QC: McGill University. Generated on June 15th, 2022. Using QGIS Geographic Information System [GIS software]. Version 3.22 (2022). QGIS Association.