Contextualizing Walkability

Comparing different sociodemographic groups'

perceptions of pedestrian space

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-Corey Dickinson

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Abstract

Walkability can be broadly conceived of as an evaluation of the suitability of a built environment for pedestrian locomotion and has recently become a popular concept across a multitude of disciplines. This evaluation is often conceptualized as a measurement, index, or tool, and has thus found itself particularly applicable within the fields of urban planning and design. This seemingly simple concept has expanded over the years, and now operates on a multitude of scales and utilizes a variety of measurement techniques, from GIS models of regional walking networks, to one-on-one interviews to explore how individuals conceptualize the idea of walkable space, to machine learning systems that evaluate imagery for desirable urban characteristics. This sprawling field now faces a challenge, with several studies concluding that walkability is becoming conceptually incoherent as it is applied in more situations—a challenge exacerbated by a lack of standardization in methodologies or definitions. Further confounding concerns of conceptual incoherence is the variability of human experience across the globe, acknowledging that different groups of people may have different values for what makes space walkable. In this context, the idea of a metric that can work in diverse places to evaluate the built environment becomes troublesome.

This study explores the aforementioned challenges in two ways: through an exploration of the diversity of literature around the subject and through an empirical study. A survey of available literature found that walkability has broadened beyond its initial conceptual confines to encompass more and more definitions over time, while incorporating additional

methodological approaches as well. Recently, numerous authors have drawn the conclusion that walkability may carry different meanings in different research settings when used according to different disciplinary approaches. Here, an empirical study was carried out that compared two groups' perceptions of walkable space, namely one in Montreal, Canada and one in Pune, India. By having participants from both locations rate large numbers of streetscape images based on their perceived walkability, and by comparing such ratings with machine-learning image segmentation results, aspects of the built environment that constituted walkable space for each group were evaluated. It was found that while there was a difference in how walkability is conceived of in terms of elements of the built environment, a common conception of general walkability exists between the two groups. A notable example of this pattern from this study is that Montrealers tended to view greenspace as a significantly more important component of walkability than participants from Pune viewed it, though both agreed that an area with pleasant greenery and little traffic was walkable. This scalar difference has important implications for future walkability work, implying that further research is needed to delineate universal walkability from contextualized walkability.

French Abstract

La marchabilité peut être largement conçue comme une évaluation de l'adéquation d'un environnement construit pour la circulation des piétons et est récemment devenue un concept populaire dans une multitude de disciplines. Cette évaluation est souvent conceptualisée sous la forme d'une mesure, d'un indice ou d'un outil et s'est ainsi trouvée particulièrement applicable dans les domaines de l'urbanisme et du design. Ce concept apparemment simple s'est développé au fil des ans et fonctionne désormais à une multitude d'échelles et utilise une variété de techniques de mesure, depuis les modèles SIG de réseaux de marche régionaux jusqu'aux entretiens individuels visant à explorer la façon dont les individus conceptualisent l'idée d'espace piétonnier, en passant par les systèmes d'apprentissage automatique qui évaluent les images en fonction des caractéristiques urbaines souhaitables. ce vaste domaine est aujourd'hui confronté à un défi, plusieurs études ayant conclu que la notion de marchabilité devient incohérente sur le plan conceptuel à mesure qu'elle est appliquée à un plus grand nombre de situations - un défi exacerbé par le manque de normalisation des méthodologies ou des définitions. La variabilité de l'expérience humaine à travers le monde, reconnaissant que différents groupes de personnes peuvent avoir des valeurs différentes quant à ce qui rend un espace praticable à pied, vient encore compliquer les problèmes d'incohérence conceptuelle. Dans ce contexte, l'idée d'une métrique qui puisse fonctionner dans divers endroits pour évaluer l'environnement bâti devient problématique.

Cette étude explore les défis susmentionnés de deux manières : par une exploration de la diversité de la littérature sur le sujet et par une étude empirique. Une revue de la littérature disponible a révélé que la marchabilité s'est élargie au-delà de ses limites conceptuelles initiales pour englober de plus en plus de définitions au fil du temps, tout en incorporant des approches méthodologiques supplémentaires. Récemment, de nombreux auteurs sont arrivés à la conclusion que la marchabilité peut avoir différentes significations dans différents contextes de recherche lorsqu'elle est utilisée, selon différentes approches disciplinaires. Dans le cadre de cette étude empirique, nous avons comparé les perceptions de deux groupes d'espaces piétonniers, l'un à Montréal, au Canada et l'autre à Pune, en Inde. En demandant aux participants des deux endroits d'évaluer un grand nombre d'images de paysages de rue en fonction de leur caractère piétonnier perçu et en comparant ces évaluations avec les résultats de la segmentation d'images par apprentissage automatique, les aspects de l'environnement bâti qui constituent un espace piétonnier pour chaque groupe ont été évalués. Il a été decouvert que, bien qu'il y ait une différence de la façon de concevoir la marchabilité en termes d'éléments de l'environnement bâti, une conception commune de la marchabilité générale existe entre les deux groupes. Un exemple notable de ce modèle est que les Montréalais avaient tendance à considérer les espaces verts comme une composante beaucoup plus importante de la marchabilité que les participants de Pune, même si les deux groupes étaient d'accord pour dire qu'une zone avec des espaces verts agréables et peu de traffic était marchable. Cette différence d'échelle à des implications importantes pour les travaux futurs sur la marchabilité, ce qui implique que des recherches supplémentaires sont nécessaires pour délimiter la marchabilité universelle de la marchabilité contextualisée.

Ch. 1: Introduction

1.1 Why is walkability important to understand?

> Walkability: a nebulous term for planning concepts best understood by the mixed use of amenities in high-density neighborhoods where people can access said amenities by foot.[1] It is based on the idea that urban spaces should be more than just transport corridors designed for maximum vehicle throughput. Instead, it should be relatively complete livable spaces that serve a variety of uses, users, and transportation modes and reduce the need for cars for travel.
>
> - Dovey et al., paraphrased on Wikipedia (2020)

Researching walkability has become a key part of urban planning, studies, and design work in recent years. This body of work seeks to explore how the concept of walkability has been operationalized, and to understand the implications of that for future research. In particular, this thesis occupies itself with the issue of contextualizing walkability. Walkability does not exist in a vacuum, and human identities and subjectivities may play a role in how it is understood. Through a review of the literature and a comparative study using streetscapes to understand two populations' perceptions of walkability, this thesis will serve to contextualize this complex concept.

1.2 The importance of Walkability

Numerous studies have explored different ways of applying and measuring the concept of walkability. Despite this variation in its definition, most studies have found that it is often correlated with a wide variety of positive quality of life indicators. This is especially true when it comes to population-level health research, in which numerous studies have shown that neighborhood walkability, however defined, is a key indicator for obesity rates, mental health, and diabetes (Creatore et al., 2016). This has been shown to be both causal and correlational – in a very direct sense, living in a "walkable" place means you are more likely to engage in physical activity regularly, and thus more likely to have better health. These same sorts of walkable places also encourage healthy living, because of other attributes (such as retail density or well-developed active transport infrastructure) associated with walkability are likely to have aspects that will encourage people to behave in healthy ways. This is particularly true for attributes associated with comprehensive conceptualizations of walkability. A narrow definition of a walkable place might just be a street with a sidewalk, but a broad definition would include spaces that contain within them mixed-use neighborhoods, green spaces, multimodal transit, and dense network grids – all urban attributes that intuitively result in more physical activity as one moves through spaces marked by these traits. Examples of this include the associations between greenspace and walkability, and greenspace and low rates of diabetes (Creatore et al., 2016).

This same associative relationship between walkability and health continues when the link between walkability and urban design is examined. Here, walkability is considered a key part of good urban design. As mentioned earlier, a comprehensive walkability concept includes many aspects of urban design that are considered positive among modern urban planning practitioners. Walkable spaces are defined by both the context around them and the walkable segment itself, and an area with high walkability will inherently positively affect the neighborhood around it. This pedestrian-focused urban design and measurement has been used to evaluate numerous end-goals of urban planning, including the quality of life of residents living in such places, the economic dynamism of a city, and the environmental aspects of the built environment (Shamsuddin et al., 2012). This link is part of the reason walkability plays a key role in active transport design, and transit systems in urban areas are demonstrated to perform far better when they are linked with walkable spaces (Frank et al., 2006; Millward et al., 2013).

Environmentally, the impacts of walkable areas of cities cannot be understated. These impacts often occur on larger scales than the pedestrian one in which walkability is measured. Numerous studies have shown that cities that are walkable are also cities with accessible public transit and with a lesser impact on carbon emissions due to reduced automobile traffic (Yamagata et al., 2019). Walkable spaces also have higher built-up density, which allows for much more efficient allocation of utilities and municipal resources than in more spread-out urban environments. Lastly, walkable cities are associated with greenspaces and parks that positively affect the environmental situation within the city and in the region at large.

Economic impacts of walkable spaces are more complex to measure but are also markedly positive. Dense mixed-use grids have higher densities of businesses that produce a larger percentage of the economic productivity of a city and provide valuable tax revenue to the municipal government (Not Just Bikes, 2022). Healthier citizens, public transit, and efficient utilities all have non-negligible impacts on governmental finances and allow for economically healthier cities to flourish.

A walkable urban environment therefore has direct multifaceted impacts on the quality of life of its residents. People living in these places are demonstrably healthier, but they also have easier access to other resources such as schools, businesses, and community centers. An important aspect of this are the ways in which walkable spaces protect residents from noise and dangerous traffic conditions, which puts people at ease. Comprehensive walkability definitions also measure the pleasantness of places, such that supposedly walkable areas that are oppressive and unpleasant (e.g. a concrete underpass) will be considered less walkable. Abstract concepts like beauty, welcomeness, and a sense of safety are all increasingly important aspects of walkability measurements. These definitions do an even better job of reflecting the ways in which complex walkability is a measurement of the many things that make some built environments good places to live in. Neighborhoods that are walkable are often shown to be places where sense of community is strongest and where neighbors know each other. This is intuitive, as a walkable place likely increases interactions between strangers and neighbors more than a car-driven neighborhood design.

1.3 Walkability as universal evaluator

As mentioned above, walkable spaces are, in almost every quality-of-life driven urban metric, good spaces. They are positive environmentally, economically, and socially. They are often beautiful and pleasant, and associated with touristic activities because of this. In many ways, walkability has become a simple measurement for a concept that modern urban planning considers important. This has been demonstrated in the section above and through numerous other explorations of both casual and correlational relationships between walkability and exterior information. This cause-and-effect relationship is almost impossible to untangle, as walkability is such a catch-all that it includes within it both elements that are derived from the ability to walk safely within an area, and elements that are derived from areas already being considered walkable spaces.

Because of this well-established correlational and causational pattern, walkability measurements have become a convenient stand-in for the measurement of other traits of the built environment. Forsyth's (2015) review of applied walkability literature found that many papers used walkability as a stand in for another measurement, underscoring how common its usage in this way has become. They identified the main motivation for walkability becoming so commonplace as a substitute was that it is multidimensional, measurable, and holistic (Forsyth, 2015). Other measurements evaluated using walkability include safety, economic investment potential, and even "desirability". What all these quantified traits share in common, and what makes walkability such a good stand-in for "positive built environment", is their preoccupation with issues around the measurement of quality of life in a spatial sense.

However, the measurements of any comprehensive scoring mechanism will inevitably face challenges being pinned down and put within a convenient box. Given the established importance of walkability as a way of measuring other things, one would expect it to have a well-established quantification and measurement system, however it is not so. Walkability remains a vague concept and is defined differently in different settings and operationalized differently by different researchers. The literature review section explores this variation further, but the different ways of measuring walkability can broadly be broken down into measurements using GIS, surveys and audits, and novel methods (many of which involve computer vision).

Part of the reason for this variation in measurement is the multitude of ways one comprehends walkability. Walkability, when it was first conceived, was assumed to be relatively universal in that it was applicable in many different contexts. Recent research has found this to be far from true. Forsyth (2015) found 27 different definitions of walkability, underscoring the extreme variation in the term (Forsyth 2015). These can vary from narrow quantitative definitions derived from grid-network connectivity or segmented imagery, to abstract interviews with one person about how walking relates to their sense of spirituality. Given these different measurements and conceptualizations, it is no surprise that it is very difficult to attribute variation in walkability to any individual urban or social trait. This challenge has helped give birth to a sub-branch of the field that seeks to dissect and evaluate critically some of the contradictions and issues with the concept (Shashank & Schuurman, 2019).

As mentioned before, as walkability has become more of a stand-in for positive aspects of a built environment (as conceived by urban planners), it has incorporated within it increasingly abstract and subjective traits. Pleasantness, safety, and welcomeness vary greatly in perception from group to group and person to person. The increasing incorporation of these abstract concepts in walkability research has led to an issue where subjectivity of experience may heavily affect how walkability is measured and evaluated. When the variety of conceptualizations is combined with this issue, the potential messiness of walkability data becomes clear, as does the difficulties associated with comparing walkability results across different studies.

1.4 Research Topics

This research is focused on the problem of subjectivity in walkability studies. This thesis seeks to evaluate the impact subjective experience may have on walkability research, given a comprehensive and modern definition of walkability applied in two very different contexts. In doing so, this study will unpack how significant an impact identity may have on these types of hybrid walkability measurements that evaluate the built environment.

Identity can be conceived of in many different ways. In this case, this research explores how sociodemographic background affects walkability measurements. Sociodemographic background is the set of circumstances that create an identity; the formative environment an individual grew up in and all the details of that place and culture that might impact how that individual sees the world. Here, this concept has been operationalized by controlling for location and formative environment – research participant populations, simply put, grew up in very different places and still live there.

Given this, it would be illuminating to evaluate if this variation in experience directly translates into different perceptions of abstract walkability variables when users evaluate similar spaces. Specifically, I ask the research question “How does one's identity and cultural background effect how walkability is perceived?” This question is explored by evaluating how users from two locations (One in Canada and one in India) rated images of pedestrian environments on a complex walkability scale. These images were also processed using a machine learning system that evaluated the contents of the images such that the visual information was turned into numerical data. These two data sets were compared using a variety of statistical techniques such that relationships between user background/location and how they rate walkability given a similar composition of images could be discerned. For example, an image mostly composed of concrete wall spaces with poor lighting and lots of trucks (a highway underpass) would likely be scored low by users rating categories such as safety or welcomeness.

This research draws on a variety of different sources, the principle two being walkability and applied computer vision literature. The background research of this study is detailed in the literature review chapter that follows this, Chapter 2. Chapter 3 contains the principal research of this study and summarizes some of the major findings. Finally, the thesis concludes with Chapter 4, which wraps the other chapters together and discusses some of the implications of this study for further research.

Ch. 2: Literature Review

2.1 Contextualizing walkability

This chapter will briefly review some of the different approaches identified in the literature to understand how walkable space is measured and defined, and demonstrate how that variation extends into issues around the identity of the individuals doing the walking. The goal of this literature review is similar to the goals of much of the extant walkability literature - to put walkability into context. This is a multi-part undertaking, as different types of walkability research have used different technical definitions of the term. Further, once the term walkability is defined, it may be heavily affected by the context in which it is studied. Walkability, as a concept, may not be the same thing for people in different places, with different identities, or speaking different languages. It may not be the same thing even for researchers examining it from different methodological and definitional angles. Moreover, it can vary conceptually for two people from the same community and family due to the subjectivity of the lived experience of an individual observer.

Thus, contextualizing walkability has been approached several different ways, and this chapter seeks to review them and give some key examples of these approaches. The first challenge of contextualizing walkability is defining the term, and literature that explores this will be reviewed. Once defined, walkability must be operationalized, and different methodological approaches to studying it are reviewed. Next beyond these steps, walkability and its variations for the walkers must be examined - these concepts have been unpacked based on walker's identity and based on their geographic location. Finally, given how knotty and complex this issue has become after reviewing all these different conceptualizations, this work reviews the subsection of literature focused on critically examining all these other issues and on picking apart how these differing approaches may affect the usability of walkability measurements.

2.2 Defining walkability

In order to explore how identity and context shapes perceptions of pedestrian space, it is necessary to explicitly define walkability, a term with a convoluted history. Broadly, the history of the idea can be understood to have evolved from early measurements of pedestrian flow towards more nuanced concepts that incorporate subjective experiences (Lo, 2009). Different definitions have accommodated different types of mobility, including movement from disabled pedestrians and various forms of non-motorized transport (Gray et al., 2012). Most of these different definitions tried very hard to establish universal measurements for walkability, although the universality is not always agreed upon (Annunziata & Garau, 2020; Iroz-Elardo et al., 2021). These different definitions have all been focused on the ease and experience of movement of different non-vehicular entities through the built environment (Lo, 2009). Common factors, as described by Lo's (2009) overview of the subject, include:

> "Presence of continuous and well-maintained sidewalks, Universal access characteristics, Path directness and street network connectivity, Safety of at-grade crossing treatments, Absence of heavy and high-speed traffic, Pedestrian separation or buffering from traffic, Land-use density, Building and land-use diversity or mix, Street trees and landscaping, Visual interest and a sense of place as defined under local conditions, [and] Perceived or actual security."
>
> (Lo et al, 2009., pp. 163)

The flourishing of the genre has led to many other definitions creeping in, with a recent review of definitions finding that walkability can be defined across 3 broad categories with 9 separate subdimensions reflecting various aspects of the term (Forsyth, 2015). The high-level categories explicitly defined in Forsyth's review were: *1) walkability definitions based on the environmental conditions that create walkable space, 2) definitions based on the outcomes from walking, and 3) definitions in which walkability is used as a proxy for another concept (*Forsyth, 2015*)*. Reviewing the broadness of scope identified by these definitions emphasizes the challenge facing researchers who seeks to clarify or contextualize walkability.

The quantification of these measurements, once they are agreed upon for a specific research setting, is just as fraught with difficulty as the task of creating a specific definition for the term. Breaking down these methodological approaches is vital to both defining and contextualizing walkability, as each approach is contingent on implied assumptions about the applicability of different types of measurement systems and the universality (or lack thereof) of the concept being measured (Lefebvre-Ropars & Morency, 2018). Walkability measurements can be categorized into several groups with subdivisions. Broadly speaking, there are measures derived from (a) GIS data, (b) human beings (surveys and audits), and (c) computer vision based systems which use novel methods to derive values (Shashank & Schuurman, 2019). Many studies use methodologies that interweave these various approaches, and there are a small number that are not categorizable within these groups (such as personal interviews or creative approaches) (Battista & Manaugh, 2017).

2.3 Methodological approaches to evaluating walkability

One of the most common methodologies for evaluating walkability is gathering data directly from pedestrian populations - on the ground surveys, interviews, extrapolations, and population statistics have all been used to evaluate walkability. There are several different approaches to surveying and/or auditing walkability, with different actors and roles in each approach, with no particular system having risen above others as a golden standard. However, several well-established systems already exist which can be assessed. Several of these systems are derived from data collected through surveys of local populations in an area (LivI et al., 2004; Maghelal & Capp, 2011). These pedestrian surveys vary greatly in scale, with some of the largest surveying hundreds of people regarding their perceptions of walkable spaces they interact with (OyeyemI et al., 2016). The largest scale human-derived walkability research stems from analysis derived from authoritative population statistics (Colley et al., 2019), which are often combined with GIS to analyze walkability characteristics and their effects – for example, combining rates of diabetes in a region with a network-derived walkability score (Creatore et al., 2016).

A different category of fieldwork-derived survey is collected by researchers themselves, who create audits and note what they see on the street. These include the most commonly used walkability tool, the NEWs survey (Cerin et al., 2006), as well as the Irvine-Minnesota Inventory tool and the MAPPA audit tool(Brownson et al., 2009; Day et al., 2006; Negron-Poblete & Lord, 2014). It is important to distinguish between different aspects of the type of data collected in both cases. Data can be divided into subjective walkability data, which reflects the feelings and experiences of pedestrians in a space, and objective walkability data, which is focused instead on the built environment and physical features incorporated in an area (Wang & Yang, 2019). Although they are often used in tandem, these types of studies are distinct from pedestrian surveys, as audit-type research methods derive data from observations of the built environment itself.

Additionally, measurements of walkability have been derived indirectly using GIS datasets and spatial analysis. These measurements are often validated through limited ground-truthing. The overall goal of these studies is to create ways of deriving walkability data without costly on-the-ground surveys (Schlossberg, 2006; 2007). Measuring walkability using GIS is derived from a mix of various factors, including building density, parks, shops, sidewalks, and other aspects of the built environment (Schlossberg, 2006). Generally, GIS-based measurements of walkability require highly robust data (Leslie et al., 2005, 2007). Arguably, the single most prevalent system for deriving mobility remotely is through analysis of street network grids; in one of its simplest forms walkability can be thought of having more options for places to move, meaning that higher densities of intersecting vertices in a network makes for a more walkable place (Hajrasouliha & Yin, 2015). This hypothesis has been well established in the literature and has even been used extensively outside of walkability studies (Barrington-Leigh & Millard-Ball, 2019). A variety of startups have come out of this thinking, most notably being the real estate tool "Walkscore" (Carr et al., 2010). The newly ascendant supporters of subjective measurement systems have argued that many of the traditional GIS-based systems may not be operable between different contexts due to subjectivity of experience, but a 2014 study found GIS can be used to compare many locations internationally (Adams et al., 2014; Krambeck, 2006).

Walkability, when considered from a GIS lens, also reflects the ways in which mapping itself may vary across cultures and contexts. Recent open-source mapping projects have attempted to reflect these variations, to differing levels of effectiveness. OSM, the data source that acts as a basemap for many types of walkability research, does incorporate within it the ability to make changes and add data types that are more appropriate for certain cultures and locations, which makes it an especially interesting option for usage in the case of Pune and the other locations examined in this work (Warf & Sui, 2010). Other excellent examples of location specific ontologies in modern mapping systems include Russia's 2gis and the MapKibera project (Schörghofer et al., 2017). Exploring how generic geographic data structures compare with local conditions is crucial, and can be easily abstracted to reflect various aspects of models (such as walkability models) derived from these different sets of data (Shashank & Schuurman, 2019).

A particularly novel approach is the usage of computer vision and machine learning techniques to examine streetscape images and to analyze them for walkability. This is a rapidly developing part of walkability studies approaches, although recent research has created a plethora of antecedents (Yin & Wang, 2016a). Recent studies on applied machine learning and google street view measurements of walkability have been shown to be highly successful (Blečić et al., 2018), as have tools derived from crowdsourced databases that assign walkability ratings to various images from GSV or similar applications (Cleland et al., 2021; Ye et al., 2019). Video footage has also become a key tool in this area, and there exist many examples of attempts to train value-assigning AI systems using GoPro footage for other uses (GiustI et al., 2016). These approaches are also interesting in that they allow the AI to assess walkability in areas that may not be considered traditional venues for walkability research (Verma et al., 2019). An excellent example of this is Verma's (2019) exploration of the audio aspect of walkability through training an AI to recognize sounds associated with walkable spaces. This same study also incorporated imagery-based computer vision analysis of walkable space, which inspired the approach within this thesis (explored in the next section) to handling remotely gathered data. Verma's (2019) algorithmic divisions of walkable space were borrowed for chapter 3's study, and were used to divide and analyze the streetscapes featured (Verma et al, 2019).

2.4 Literature focused on contextualizing walkability

Much of modern walkability literature skips over a close examination of definitional and methodological issues, and proceeds directly into the most complex aspect of contextualizing walkability: answering the question “ what, if anything, causes understandings of walkable space to vary?” This question, and the ways of answering it, are often predicated on a basic assumption about the nature of walkability, which shapes all other aspects of this research - a subjective or objective approach to the concept. Subjective walkability can be unpacked by examining how identity seems to affect the measurement, and objective walkability focuses on how it can be generalized (Iroz-Elardo et al., 2021). The difference between these two categories is similar to the difference between human-derived measurements and those based off of geospatial data, or any of the other dichotomous concepts existing within pedestrian studies spaces - it is a difference between a seemingly quantitative measurement (Geographic space/ GIS/ location) and a seemingly qualitative measurement (Human experience/ Surveys/ Identity). These two perspectives arise again and again –and the issue of subjectivity vs objectivity seems to haunt all discussions of the concept (Ewing & Handy, 2009). This tension is not limited to the realm of walkability, as many other fields (including the population-level health science research that originally inspired walkability studies) face similar dichotomies. Walkability indices, particularly those that are built primarily from geospatial data and imagery, are generally assumed to be derived from objective facts about space and thus may poorly account for subjective perception of individuals and context (Manaugh & El-Geneidy, 2011).

Untangling the importance of subjectivity within walkability studies is a crucial part of contextualizing walkability, and a burgeoning category of literature has explored this. Notably, Dias et al found that many walkability indices do not do a good job of accommodating individual subjective perception (Diaz & Diakopoulos, 2019). Numerous studies have shown that walkability perceptions vary depending on walkers' identity and ability to walk (Ewing & Handy, 2009; Handy et al., 2006; Manaugh & El-Geneidy, 2011). Other studies, as mentioned, have shown that individual perceptions of space can vary greatly due to sociodemographic factors such as gender and race (Handy et al., 2006; Lefebvre-Ropars & Morency, 2018; Tong et al., 2016). Previous attempts to evaluate the impact of personal lived experience on perceptions of urban space have fallen into two broad categories - attempts to contextualize walkability based on individual identity and attempts to contextualize based on geographic location. Both of these are interwoven, as, for example, culture is in many ways partially a product of geographic background (Diamond, 1997).

Simultaneously, it must be noted that many studies have found that to some level objective walkability often outweighs subjective perceptions in importance. Even when controlled for neighborhood self-selection and identity features, individuals often agree on what is and is not walkable (Frank et al., 2006; Handy et al., 2006). Objective walkability measurements often seem to line up with common-sense perceptions of the concept, and support the underlying assumptions of GIS-based generalized walkability approaches (Adams et al., 2014). One especially relevant example of this is the global walkability index, designed in 2006 to attempt to capture walkability within any context – and shown to have moderate effectiveness (Krambeck, 2006). Drawing the line between where the objective portions of walkability end and the subjective portions begin is extremely challenging, and is unlikely to be easily resolved any time soon.

2.5 Literature exploring Identity and context in walkability

The role of identity and walkability has been extensively studied, and in some ways has been one of the major focal points of research within the field in recent years (Forsyth, 2015). Most research that seeks to contextualize walkability in this way approaches the issue by studying how one identity group perceives walkable space. Some research in this regard takes an additional step to compare the differences in perceptions across groups, but this is less common, and due to differing definitional and methodological approaches it can be argued that the results of these studies are not necessarily comparable (Adlakha et al., 2016; Shashank, 2017; Shashank & Schuurman, 2019).

The range of individual identity categories explored varies widely. Broad comprehensive literature reviews conducted in the past few years, since the research became a mainstream part of urban planning, have established that identity and social characteristics of populations being studied are often a major component of contemporary walkability (Adkins et al., 2019; Shields et al., 2021). Forsyth (2015), in her review of different definitions of walkability, found that different definitions of walkability may be more suitable for different categories of walkers – i.e., different walks for different identities.

The conclusions of this vein of research often find that identity factors do indeed affect walkability perceptions. A study in Phoenix found noticeable differences in the understanding of walkability across racial groups in the same city, even those that lived in similar neighborhoods (Adkins et al., 2019). Numerous studies have sought to evaluate how sociodemographic factors affect walkability, including studies done in Montreal, and have often found that walkability scores are very different depending on the walkers' class (Manaugh & El-Geneidy, 2011). Age, too, seems to have a major effect, with a broad and robust sub-genre of the field fixated on senior walking patterns and urban adaptations for senior walking (Van Holle et al., 2014). Lewis, comparing purpose of trip, age, and ability, found that different identities had different needs depending on the reason for walking (Lewis et al., 2020). Gender identity, regardless of class, sharply divides walkability, with Adlakha's (2020) paper finding that women in India walk for utility far mor than men do, a disparity that is also reflected globally. Some research has even found that individual identity can affect subjective perceptions of walkability and throw off scores, potentially indicating major issues with the consistency of some common walkability scores (Battista & Manaugh, 2019; Manaugh & El-Geneidy, 2011).

2.6 Literature exploring geographic location, mapping, and context

Context, especially when it comes to walkability, is heavily dependent on geography, as different geographic settings shape different identities and cultural patterns. The importance of geography in walkability research has not been ignored, and location-dependent walkability research is booming - a cursory study of walkability papers utilizing the NEWS system found that a about a third of all papers had modified versions for a specific context, and 75% of studies in middle income countries used locationally-focused adaptations of generalized approaches (Almeida et al., 2021). Both implicitly in the process of adaptation and explicitly within the text, these studies engage with the idea that walkability varies depending on the walker.

Location-focused walkability research often engages with the idea that walking may be different in “developed” places and in “undeveloped” places (Almeida et al., 2021; Barrington-Leigh & Millard-Ball, 2019). Several studies have engaged in trying to account for this and find ways of applying walkability in a broader sense, including the “Global Walkability Index” study and the “IPEN international study” (Adams et al., 2014; Krambeck, 2006). Critical approaches to the subject have questioned the effectiveness of these types of solutions, arguing that the subjectivity issue means that it would not be possible to create an index that can be applied globally, although the proponents who develop these indices have found that their approaches seem to work in many different contexts (Shashank & Schuurman, 2019).

These explorations are sometimes framed as a subtle critique to the idea of objective walkability, arguing that because contexts vary the same walkability index or audit may not be applicable (Shashank & Schuurman, 2019). This supposition has been supported within pedestrian studies and urban planning, but evidence for the lack of consistency for measurement across different geographic contexts has come from many other fields, including anthropology and sociology (Graeber & Wengrow, 2021). From within geography, critiques of mapping systems themselves are applicable in this case as they demonstrate how the basic quantification system being used may predispose the results (Harley, 1989). Much research has established the inherent biases of most mapping applications, many of which were developed in the global north with very specific ideas about how a street or a city should be shaped. These mapping systems do a poor job of incorporating non-western types of built environment (Zheng & Zheng, 2014), which means that any of the more objective-style walkability measurement systems may miss crucial details. No mapping system is immune from these problems, from google maps to proprietary government data (Dodge & Perkins, 2015).

The techniques used to contextualize walkability in various locales vary, but more often than not are manifested as adaptations of generalized audits and surveys for a specific geographic context (Adlakha et al., 2016; Van Holle et al., 2014). These audits and surveys are grounded in the human-derived conceptualization of walkability, and thus it is a natural extension of that logic to adapt a survey or audit intended to capture human perceptions to specific populations and/or geographic settings. Dozens of these types of adaptations exist, but many follow similar approaches based on the NEWS scale (Almeida et al., 2021). Common techniques for adapting a survey or concept to a certain local context are focused on incorporating questions about specific local types of built environment that may not exist elsewhere, or attempting to capture variations in class and space usage that may distinguish a certain population from another (Iroz-Elardo et al., 2021).

This study aims to explore the measurability of walkability across two very different contexts: Pune, India, and Montreal, Canada. Recent contextualized studies of walkability have been performed in both countries - indeed, measuring walkability in Asia has been a hot topic in recent years, with plenty of literature specifically focused on India (Bharucha, 2017; Pandey, 2016). This is due to the rapid urbanization of the region, and the increasing reliance on cars by an ever-growing portion of the population (Tong et al., 2016). For Example, Adlakha helped develop a country-specific adaption of the global NEWS walkability survey (2016). In Pune specifically, several papers have tangentially referenced walkability and its applications to the city (Jain & Patil, 2015; Ramakrishna Nallathiga et al., 2015).

Recently, papers focused on explicitly examining walkability within Pune as a tool toward critiquing other aspects of urban design, demonstrating the value of applied walkability approaches towards influencing public policy (Pathak et al., 2021). A recent important example of the application of this vein of research is Clean Air Asia's efforts to create comprehensive indices of walkability across different Asian cities (Adlakha et al., 2016). Whether or not this is doable is still up for debate, as the CAA index has been found to be lacking by subsequent research (Dey & Bhowmik, 2018). One of the most interesting papers exploring subjectivity and walkability in a south Asian context has been Das and Islam's (2018) paper on the walkability of

Hindu pilgrimage routes in India, the concept of which is a perfect example of why subjective experience and culture can heavily impact walkability measurements.

The other location within the study, Montreal, has also seen extensive investigations of walkability in this context (as has Canada and North America in general), with some of the most cited walkability studies originating in a Canadian setting (Millward et al., 2013). Most investigations of walkability within the Canadian context treat the Canadian built environment as a default form of walkable space, with only a handful seeking to identify the ways in which northern north American cities represent a specific walking context (such as the presence of extreme snowfall and cold combined with suburbanization) (Takacs, 2017). Walkability studies were originally rooted in developed-world concepts of urban space, and Canada was the site of many of the early studies on walkability research. This means that Canadian cities represent a model for the subjectivity-blind concepts of walkability recent research has sought to define itself against (Diaz & Diakopoulos, 2019). In Montreal, several studies have examined walkability, although none have attempted to create a model specifically for a Quebecois/Montreal geographic context. Of particular interest is "Using Embodied Videos of Walking Interviews in Walkability Assessment", which shows that travel behavior is not predictable with just walkability scores alone – individual subjectivity has the potential to play a major role in walkability perceptions (Battista & Manaugh, 2017).

2.7 Literature beyond context: Metawalkability research

Given how sprawling the concept of walkability has become, it is no surprise that critical and meta-analytical branches of the field have flourished in recent years. The tension between subjective and objective approaches has not gone unnoticed, and the breadth of the field has invited examination, subdivision, and critique. Numerous scholars have attempted to survey different parts of the field and summarize what is consistent and what is not, leading to the establishment of several comprehensive literature reviews of the extant research (Lo, 2009; Maghelal & Capp, 2011; Tong et al., 2016) These papers generally orbit the same points and find the same conclusions; that walkability is an imprecise index that connects several other important urban planning concepts and metrics (Dovey & Pafka, 2020).

Many of the early comprehensive literature reviews, undertaken just as the field was maturing in the late 2000's, serve as mere overviews of the subject and fail to push towards critical depth (Krambeck, 2006; Lo, 2009). It is only recently with the broadening of the field that more probing literature has arisen (Annunziata & Garau, 2020; Iroz-Elardo et al., 2021; Shields et al., 2021). Wang and Yang's 2019 paper "Neighborhood walkability: A review and bibliometric analysis" is one of the most thorough recent examples of walkability research assessments (Wang & Yang, 2019). Importantly, it finds inconsistencies in the definitions and methodological operationalization of walkability across 136 recent walkability studies (Wang & Yang, 2019).

Importantly, these many review papers have fed off each other, with the general trend in walkability research moving from the establishment of the major indexes before 2010 towards more and more meta-analysis, literature reviews, and examinations of subjectivity (Iroz-Elardo et al., 2021). Currently, it can be observed that the research landscape is populated with many studies that consist of combinations of existing measurements, with the most recent development towards critical examination and broad meta-analysis coming much more recently (Iroz-Elardo et al., 2021). The rise of subjectivity in walkability has mirrored the rise of identity and subjectivity in other social sciences, allowing for the examination of the built environment to be applied within identity-focused research in other fields.

Arguably, the most significant paper on the subject in recent times has been Schuurman and Shashank's (2019) paper, which is the most critical meta-examination of the subject yet attempted and compares several competing walkability indices to look for mutual intelligibility in measurement types. It's findings in many ways provide the grounding to which this research responds, and perhaps indicate potential problems that may prevent global walkability measurements from being comparable (Schuurman and Shashank, 2019).

Taken together, Schuurman et al. (2019) and Wang et al. (2019) represent the most recent and most comprehensive assessment of the current state of walkability research: simultaneously over-researched in many regards but surprisingly underutilized in others. Both concluded that one of the most promising aspects of walkability research today is investigations of the applications of the index beyond the relatively narrow bounds inside of which it has been explored. And, most importantly, both conclude that the line between subjective and objective walkability is not yet well defined – and may never be.

Ch. 3: Geographic identity and perceptions of walkable space

3.1. Introduction and background

As stated earlier, Walkability, as a subject, has grown enormously in importance across many different academic fields in recent times. Originally arising out of public health literature (Livi et al., 2004), it has become an integral part of the discussion within modern urban planning. In particular, walkability is now considered to be a vital aspect of what makes the built environment "livable" and is a cornerstone of the sub-field of active transport (Barrington-Leigh & Escande, 2018).

So then, what is walkability? The previous chapter has shown that many have tried to define this nebulous concept, to varying levels of effectiveness. These papers have taken a variety of different approaches, and have thus diagrammed and dissected the concept. Numerous novel indexes have been proposed, integrating a wide variety of different types of technologies and methodologies. At this point, an appraisal of the field reveals a sprawling literature loosely connected by a handful of central threads. Additionally, it includes numerous articles that attempt to survey other literature, resulting in a corpus that utilizes a wide and sometimes inconsistent set of definitions (Lo, 2009; A. Shashank & Schuurman, 2019; Wang & Yang, 2019).

The measurement of the concept of walkability has varied greatly and diversified in the time since it first began being applied widely in academic literature. Walkability is calculated across many scales and utilizes a variety of different methods. Walkability measurements can be categorized into several groups with subdivisions. Broadly speaking, there are measures derived from GIS data, from on-the-ground surveys, and from visual-image based systems (which use novel methods to derive indices) (Wang & Yang, 2019). These methods are often mixed together and used in tandem, allowing for the development of very complex indices. The resultant indices have themselves been applied in numerous situations, and have found applicability in fields outside the original urban-planning focused contexts in which they were proposed (ShumI et al., 2015).

In the wake of the ascendancy of walkability as a metric has come the rise of literature questioning some of the recently established conventions in this field (Diaz & Diakopoulos, 2019). This has focused on a variety of different issues with the metric - walkability is often measured using a relatively limited set of methods, and is often conceptually predicated on broad assumptions about what walkability is. This has evolved to the point where some scholars have pointed out the lack of consistency and standardization across the field rendering the word incomprehensible, with Shashank and Schurmaan (2019) concluding that walkability indices may not be mutually intelligible:

> We found that definitions and methods utilized in walkability indices were not explicated with sufficient detail. In other words, the assumptions contained in the indices should be made transparent. At the present, algorithmic calculations used in walkability indices are black boxes. This research has revealed the methodological steps used to calculate three common indices and, in the process, illustrated that the results are fundamentally incongruent due to differences in definitions that have trickled through to the final walkability scores. This points to the need for more research

combined with greater skepticism about the voracity of walkability indices. However, we open the door for local indices to be developed that better represent the study context.

(Shashank & Schuurman, 2019, pp 152)

These inconsistencies have been highlighted in a flurry of recent scholarly work that has sought to highlight issues with various walkability indices and methodologies. Shashank and Schurman found that different walkability methodologies, when applied to the same area produced different results indicating which areas were and were not walkable (Shashank & Schuurman, 2019). Several studies have found that different individual people from different cultures may define the word “walkable” in different ways, depending on their background (Sepe, 2009). A particularly striking example of this explored walkability perceptions of female Bangladeshi Garment Workers, who’s quality of life is heavily dependent on how walkable they perceive space to be (Shumi et al., 2015). Sepe’s seminal work on “placemaking” found that perceptions of the built environment are heavily affected by identity, and thus that walkability may vary across both physical and psychological space (Sepe, 2007). Taken together, these studies (among many others) indicate that walkability itself is nebulous and ever shifting, and is often predicated on the assumption that walkers are a homogenous group.

In the context of this paper, critiques of walkability that focus on issues related to how it is impacted by identity are of particular interest. For the past several decades, there has been a lot of focus on how different demographics' personal experiences affect how we perceive the world. These have included examinations of the impact of age, gender, and socioeconomic status on the perception of urban space (Adlakha & Parra, 2020; HidayatI et al., 2020). Following this line of questioning, this work seeks to establish how great of an impact identity, particularly cultural identity, has on walkability measurements. Very little of the aforementioned work that has sought to contextualize walkability has been comparative. Identity and location have been used as a lens to examine the concept since its inception, and recent reviews of the subject have identified localized walkability indices as the next frontier for the field (Wang & Yang, 2019). Later examples applied this same formula in many different locations, although they often used inconsistent methodological strategies for quantifying walkability as a measurement (Iroz-Elardo et al., 2021; Lefebvre-Ropars & Morency, 2018, Dovey, 2020). Despite this movement, there have been few attempts to synthesize these patterns. Given this, this study seeks to be one of the first to enter this debate and contribute to the data establishing how walkability is perceived differently across different groups of people. Specifically, I ask the research question “How does one's identity and sociocultural background affect how walkability is perceived?”

This study thus seeks to compare two groups from two different cultures and to determine how their understanding of walkability differ. These two groups are located in Pune, India and Montreal, Quebec. These locations were chosen because of the significant differences in their historical trajectories, the difference in their built environments, and the difference in societal structures of those who move through both spaces, as well as the existence of collaborative research partners. Through the quantification of each group's perception of walkable space, it can be established what underlying factors may drive their perceptions. Previous literature has sought to contextualize walkability in both of these locations, albeit in a non-comparative way. In a south Asian context, there has been a recent flurry of contextualization, including several studies focused on Pune specifically (Adlakha & Parra, 2020;

Bharucha, 2017; Pathak et al., 2021). The same applies for Montreal, with studies exploring it locally in 2011, 2017, and 2019 (Battista & Manaugh, 2017, 2019; Manaugh & El-Geneidy, 2011).

3.2. Methodology

The investigation of cultural perceptions around walkability required gathering data from both the target populations. The design of the survey evolved over time, and was heavily affected by the COVID-19 pandemic. Initial conceptualizations of the data gathering process involved in-person surveys on the streets of both Montreal and Pune, with the surveys being compared with video footage collected via GoPro and processed with image-segmentation tools. This methodology would have been similar to that found in Verma et al.'s (2019) study, which heavily influenced the trajectory of this research, particularly in terms of the computer vision components (Verma et al., 2019).

In both locations, two separate iterations of an online survey of perception of various facets of walkability, based on a series of streetscape images collected through the user-sourced Mapillary platform, were administered. The Mapillary platform was chosen rather than Google street view as it provided better coverage of streetscapes for the areas of interest (Mapillary, 2022). The survey data set sought to collect information that classified how individual pedestrians perceived various aspects of streetscape that feed into walkability indexes, and to be able to classify the streetscapes through image segmentation. The survey tried to capture several major aspects of pedestrian perceptions of urban spaces that are common components of walkability metrics: Crime and traffic safety, infrastructural navigability, aesthetics, and comfort.

3.2.1 Survey Design

The survey questions were modeled after multifaceted understanding of walkability, derived from seminal survey-based walkability studies (such as the NEWs study) and from large literature reviews of many studies that sought to define the term (Almeida et al., 2021; Cerin et al., 2006; Lo, 2009). Similar surveys have also sought to collect data by breaking it down into some of the essential aspects of walkability (Iroz-Elardo et al., 2021). The study asked respondents to rate a streetscape image on 6 factors, from a scale of 1 (least) to 5 (most): Safety From Crime, Safety From Traffic, Physical Navigability, Aesthetic Pleasantness, Welcomeness, and Walkability. The last rating factor, walkability, was not explicitly defined for the participants. This decision was made so that it could be determined how they themselves would rate something, using their own personal definition of what “walkable” meant. A “catch question” focused on the number of cars visible was also included, which was deployed once every 9 images in the sequence. If users answered this question incorrectly a large portion of the time, their data was later discounted as it can be assumed that they were not paying close attention to the exercise.

The construction of the survey was done using a JavaScript-based online coding tool called "SurveyJS." (Iroz-Elardo et al., 2021; SurveyJS.io, 2022). This survey was developed from scratch, as existing survey tools struggled with the volume of inputs needed to rate many thousands of images. The images were served into the survey application from Mapillary's API, and proceeded sequentially through the list of images selected within geographic scope of the study areas. Entries were alternated between Montreal and Pune, and were staggered such that each participant rated 40 of the same images as the previous participant and rated a number of new images within a one hour timespan. This setup ensured that many images were rated multiple times by multiple users from the same location, something considered a best practice in this type of study. Additionally, it is noted that the Pune participants and the Montreal participants began at different points in the image stack, meaning that they did not rate any of the exact same images. However, the images were from the same randomly shuffled database and were alternated from both locations, meaning that both groups tagged a representative sample of the images from the database and thus the results can be trusted to be coherent between the two groups.

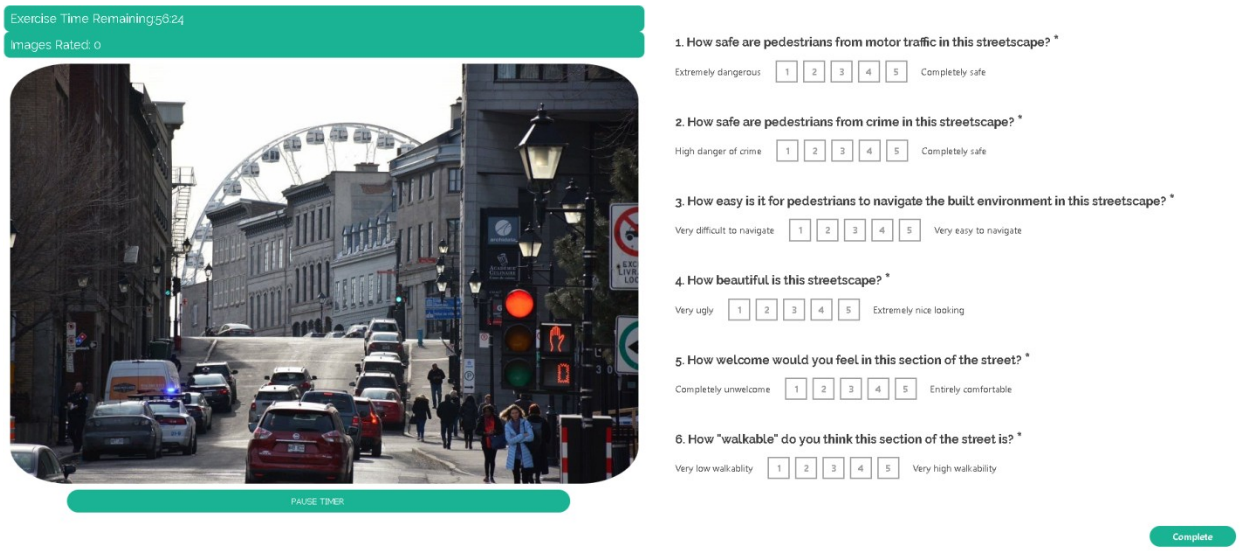
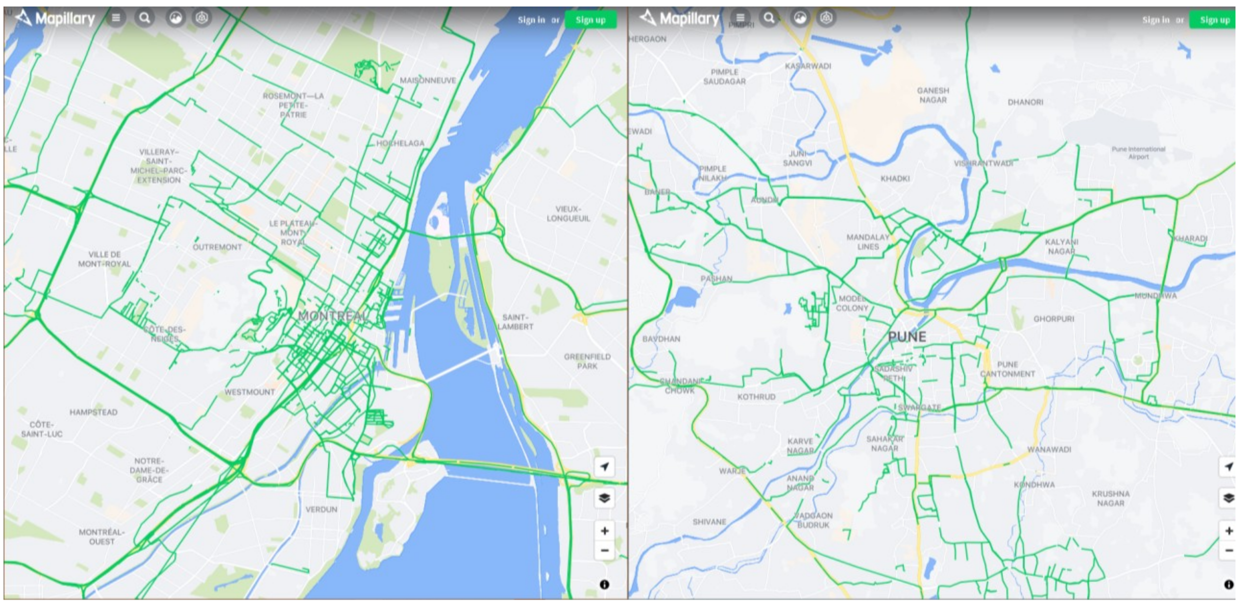


Figure 1: Screenshot of Final Survey Tool

3.2.2 Geographic scope and image processing

The areas of interest were selected from the maps below, and sought to capture a representative area from each of the two metropolises. The areas all feature a mixture of urban core, highway, suburban development, and semi-rural areas. Images from the green segments in the maps below were randomly extracted using a python script that accessed the Mapillary API (Mapillary.com, 2022). A total of approximately 10,000 Images were extracted from each location and were available for usage in the survey. The same python script also screened the images for unacceptably blurry images, with a blur threshold of “100” selected as the maximum blur level - images outside of those parameters were discarded. This detection was accomplished using the “variance of laplacian” image calculation technique from OpenCV’s python library, which compares pixels with those around them within a matrix to determine the blurriness level and produces a value indicating variance across the image between neighboring pixels (OpenCV, 2022). While the system stored these images in an external database, it served them to participants via the Mapillary API which referenced a list of image addresses stored in a Github database.



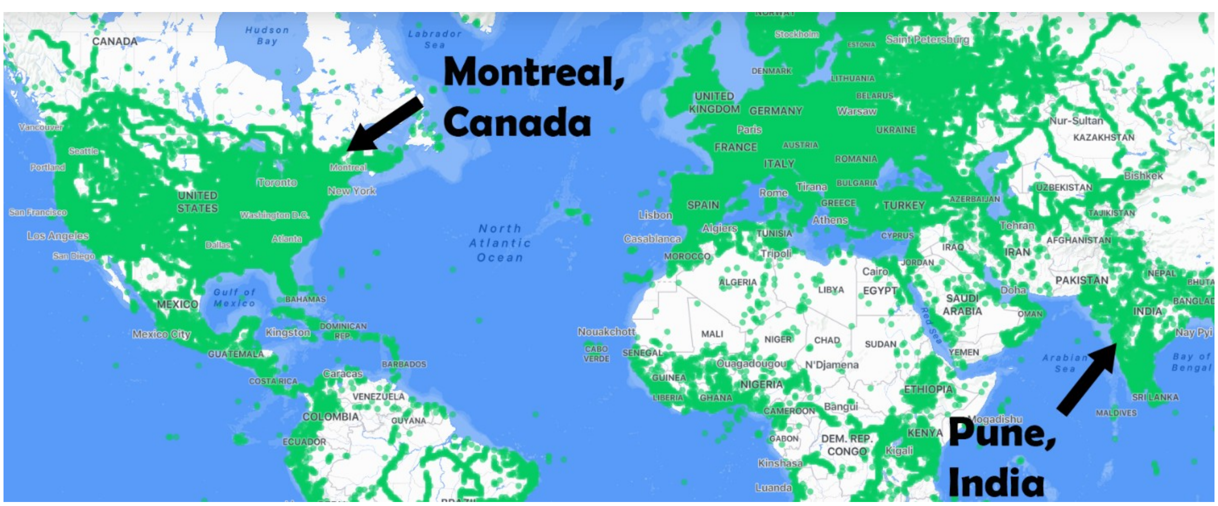


Figure 2: Maps of locations of interest within Pune and Montreal. Green lines represent segments with Mapillary imagery data. (Edited from Mapillary.com, May 2022)

3.2.3 Survey implementation

Between March and May of 2021, the images were evaluated by two groups of participants for the walkability attributes mentioned earlier using the online survey. The participants were recruited from students at universities in Montreal and Pune, and were offered the same compensation (20 CAD) for participation. Additionally, they were offered the chance to win a gift card to a local business selected in a random draw, with one 100 CAD card (or its equivalent in INR) for each city. The recruitment process also sought to remove students that had not spent most of their lives in the locations of interest (i.e., in Pune or in Montreal). In the end, the participant pool included 74 students from 7 different universities across both locations.

A total of 3226 unique images were tagged across 71 valid participants, with 54.1% being from Montreal and 45.9% being from Pune. Figure 3 shows the breakdown of total data collected, along with the demographics of the participants. Although options were provided for other/self-defined gender identity categories, no users fell into those categories. The results had a heavy gender bias as 79% of the respondents identified as female. Three users were removed as they failed the catch question test. A total of 6902 datapoints were valid for analysis, of which 59% came from the group of users from Montreal. Despite this, Pune users on average tagged more images per person than Montrealers, with Pune users tagging 108 images on average per person and Montrealers tagging ~88 images per person.

Data on the formative and current locations of users on an ordinal scale between rural and urban upbringing was also collected. This data was collected to check the hypothesis that the built environment of a user's childhood might affect how they perceive urban spaces (Broom, 2017). The average user formative location was higher for Pune users (2.81) than Montreal users (2.14), indicating that Montreal participants came from a less urban background. The average age for Montreal participants was 23, which was slightly older than Pune's average of 19.

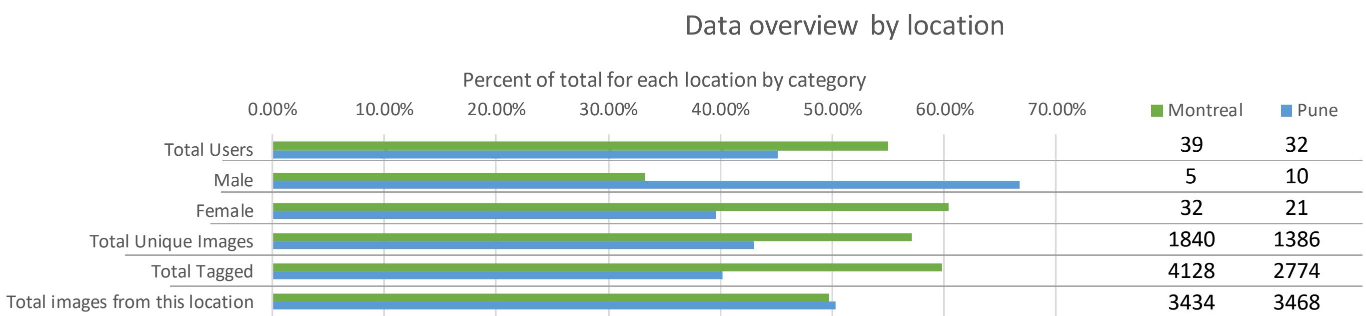


Figure 3: User and location statistics

3.2.4 Segmentation tool

A recent development in walkability studies has been the application of computer vision technology. Computer vision is a sub-field of machine learning that seeks to explore how computers analyze images and recognize patterns within images (Somasundaram et al., 2013; Ye et al., 2019; Yin & Wang, 2016b). This technology is invaluable in this case, as it was used to compensate for the inability to extract data from in-person study due to the COVID-19 pandemic.

We utilized computer vision tools to abstract data about streetscape imagery, such that it can be analyzed. Semantic segmentation, a type of computer vision that analyzes picture contents using a machine learning algorithm, provides us data on the contents and makeup of the images. This data can be aggregated and compared with the participants' survey results, meaning that large amounts of data points about users' perceptions can easily be compared with the actual content of a streetscape image.

The specifications of the algorithm collection were taken from Verma et all (2019 a,b), These pretrained models performed object detection tasks, semantic segmentation tasks, and image classification tasks. Each task was trained on different data and used different ML models. The Object detection model sought to identify and count certain elements in the image, and was trained on COCO dataset (Common Objects in Context) and utilized Faster RCNN NAS (Lin, Maire, & Belongie, 2014). The Semantic Segmentation task divides the image into polygons and counts what percentage of the image consists of a certain category, and was trained on ADE20K, and utilized PSPNet (Zhao, Shi, & Qi, 2017). The Image Classification task determines what is in an entire image and assigns a probability to that, and was trained on the databases called Places 365 and utilized OpenCV (OpenCV, n.d.). Altogether, this package produced 24 different measurements of the content of an image that can be compared against the user data results.

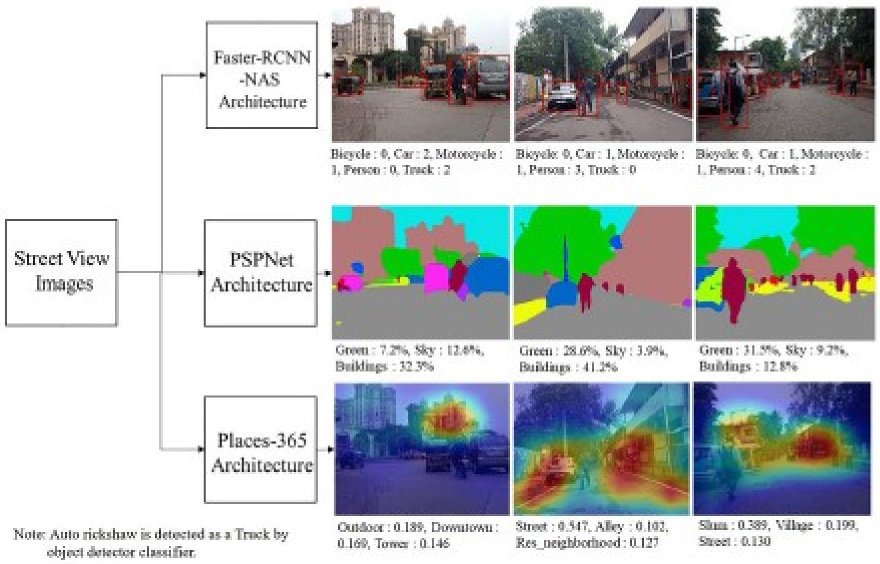


Figure 4: Computer-vision segmentation tool feature extraction from streetscapes overview, from Verma et al. (2019b)

3.2.5 Statistical analysis

Once the tagging data was collected, the segmentation tool generated values for 24 different factors related to the contents of an image. By doing this, data about the composition of an image could be linked with user-derived image tags and ratings. The data was then reorganized in several ways, including the creation of both a dummy variable system representing user/picture location, and a binning system in which ratings were grouped by user/image combination. The segmentation factors are represented in Table 1.

Segmentation Value Name	Segmentation Model Definition
built_other_ic	Probability of the image being classified as Downtown/Embassy/Plaza classes obtained from IC task.
green_other_ic	Probability of the image being taken in Forest path/Forest road classes obtained from IC task.
tree_ss	Percentage of pixels classified as trees in a street view image.
street_ss	Percentage of pixels classified as street and sidewalks.
built_ss	Percentage of pixels classified as buildings.
Saturation_mean_llf	The mean value of saturation dimension in the image when converted to HSL color space. Saturation defines the range from pure color to gray at a constant lightness level.
Lightness_std_llf	The standard deviation of lightness dimension in the image when converted to HSL color space.
Saturation_std_llf	The standard deviation of saturation dimension in the image when converted to HSL color space.
canny_edge_llf	The ratio of pixels detected as edges to the total no. of pixels in the image.
no_of_blobs_llf	The no. of groups of connected pixels in an image that shares some common property.
market_ic	Probability of the image being classified as Bazaar indoor/Bazaar outdoor/Flea market/Market outdoor classes obtained from IC task.
bicycle_od	Total no. of bicycles detected in the image in OD task.
motorcycle_od	Total no. of motorcycles/scooters detected in OD task.
person_od	Total no. of persons detected in OD task.
slum_ic	Probability of the image being classified as Slum/Alley/Junkyard classes obtained from IC task.
bus_od	Total no. of buses detected in OD task.
car_od	Total no. of bicycles detected in OD task.
traffic_light_od	Total no. of traffic lights detected in OD task.
truck_od	Total no. of trucks/auto rickshaws detected in OD task.
Hue_std_llf	The standard deviation of hue dimension in the image when converted to HSL color space.
Lightness_mean_llf	The mean value of lightness dimension in the image when converted to HSL color space. Lightness is also referred to as value or tone and represents the brightness of colors.
sky_ss	Percentage of pixels classified as sky.
nature	The percentage of pixels belonging to natural elements such as sky, tree, grass, earth, mountain, plant, water, sea, sand, river, flower, dirt track, land, waterfall, animal, and lake classified from SS task.
Hue_mean_llf	The mean value of the hue dimension in the image when converted to HSL color space. The term Hue is used to refer pure spectrum colors.
others_ss	Percentage of pixels classified as other remaining outdoor classes as given in ADE20K dataset such as advertisement boards, billboards, and traffic signals.

Table 1: Segmentation Factors and Descriptions

An important aspect of this step of the process was the simplification of image-segmentation derived data through factor analysis. Utilizing SPSS's factor analysis tool, factors were reduced from 24 variables to 9 different factors. This step mixed all of the different variable data types, including object detection data (counts), semantic segmentation tasks (percentages of image occupied by a class), and image classification data (confidence values.) This mixing of data types was later accommodated for in the processing through the standardization of statistical results. Each of the new factors reflects a multifaceted aspect of a streetscape. These new factors can be seen in Table 2.

	Factors								
Variables	**1. Pedestrianess**	**2. Urbanness**	**3. Image Clarity**	**4. Liveliness**	**5. Complexity**	**6. Traffic**	**7. Brightness**	**8. LV Presence**	**9. Informality**
built_other_ic	0.095	-0.377	-0.096	0.003	0.105	-0.184	0.218	0.066	0.684
green_other_ic	0.346	0.497	-0.033	-0.178	-0.015	-0.157	0.078	-0.234	0.02
tree_ss	0.478	0.672	0.039	0.072	-0.015	-0.02	0.366	0.004	-0.09
street_ss	0.051	-0.141	-0.134	0.022	-0.903	0.185	-0.136	0.033	0.027
built_ss	0.167	-0.863	-0.098	0.034	0.006	-0.141	0.062	-0.077	0.092
Saturation_mean_llf	-0.107	0.146	0.908	-0.088	0.161	-0.053	-0.038	-0.097	0.022
Lightness_std_llf	-0.423	0.118	0.207	0.03	0.001	-0.055	0.713	0.196	-0.054
Saturation_std_llf	0.094	0.029	0.871	0.038	-0.037	0.04	0.182	0.07	-0.105
canny_edge_llf	0.763	0.215	0.17	0.152	0.229	-0.241	-0.135	-0.036	-0.119
no_of_blobs_llf	0.559	-0.006	0.459	0.3	-0.004	-0.167	0.005	0.074	0.107
market_ic	-0.022	-0.255	0.11	0.439	-0.064	-0.074	0.119	-0.059	-0.251
bicycle_od	0.051	-0.011	-0.079	0.518	0.071	-0.037	-0.043	-0.03	0.092
motorcycle_od	0.082	-0.022	0.034	0.784	-0.04	0.018	0.026	0.008	-0.139
person_od	0.086	0.004	0.01	0.827	-0.01	-0.025	0.016	0.067	0.018
slum_ic	0.071	-0.337	-0.099	0.116	0.12	-0.218	0.037	-0.009	-0.615
bus_od	0.022	-0.017	-0.02	-0.017	0.035	-0.119	-0.072	0.785	0.192
car_od	-0.101	-0.054	0.009	-0.109	-0.053	0.782	-0.035	0.055	0.158
traffic_light_od	-0.208	-0.122	-0.017	0.001	-0.094	0.123	-0.07	-0.063	0.38
truck_od	-0.029	0.005	0.002	-0.008	-0.003	0.22	0.044	0.703	-0.186
Hue_std_llf	0.423	-0.244	-0.282	0.226	-0.044	-0.03	0.091	0.332	-0.189
Lightness_mean_llf	-0.292	-0.054	0.035	-0.021	-0.076	0.043	-0.777	0.157	-0.063
sky_ss	-0.858	0.209	0.175	-0.069	0.169	-0.193	-0.091	0.04	0.081
nature	-0.186	0.828	0.156	-0.076	0.192	-0.355	0.118	-0.044	0
Hue_mean_llf	-0.453	0.06	0.461	0.01	0.16	0.293	-0.189	-0.108	0.123
others_ss	0.039	-0.127	0.017	0.058	0.694	0.544	-0.115	0.13	-0.144

Table 2: Factor Analysis Results

At this point, additional statistical processing (i.e., regression models) was performed using IBM's SPSS to analyze the relationship between user characteristics and the data (IBM SPSS, 2022). A model was created that ran regressions on the relationship between each of the user-tagged values (binned into groups) for a streetscape, and each of the 9 derived factors as discussed above. The model was run with various combinations of the factors. Additional models were also run with different user-demographic variables to see if any major trends stood out. This included running regressions on all data combined, to determine which user-identity factors had the strongest influences on the data. Additionally, these results were cross-checked with regressions and correlations run on all of the 24 individual variables before they were compressed into the 9 factors, to check if any errors occurred during processing. This process was repeated on bins consisting of all the data coming from both population groups. These 9 factors explained a total of 68% of the variance within the data, with the first three accounting for more than a third of all variation.

An analysis of the derived components revealed an interesting trend in factors, which plays heavily into the final results. Many factors consisted of combinations of information that did not necessarily make intuitive sense. For example, the components included three separate categories that highlighted nature - one that seemed to be measuring the percentage of the image that consisted of mostly natural vegetation, and one that measured the amount of the image that contained within it large amounts of well-lit trees and greenery. These complex factors are multifaceted, which lines up well with many of the conclusions of extant walkability research. Lighting played a major role, and while discounting it was considered, some measurements associated with lighting and image composition proved useful for explaining some of the derived components - for example, importance of edges and complexity. Determining what these factors represent can be difficult (Neill, 2015). Factor analysis values indicate both positive and negative correlation, giving us a more nuanced idea of values. After analysis of all 9 factors, they were categorized as shown in Table 3.

Fa # & % of Variance	Sample High MTL	Sample High PUN	Sample Low MTL	Sample Low Pun	Positive Vars	Negative Vars	Explanation	New Name
FA 1 14.15% of variance (Total 14.15%)					+ Built_SS + + Green_Other_ic + + Tree_SS ++ Hue_std + + + Canny_Edge + + + No_of_blobs	- - Sky_SS - - Hue_mean - - lightness std - - lightness mean - - traffic light od - nature - saturation - Car	Complex, seems to be tracking the overall trend between pedestrian pathway in nature and highway	Pedestrianness
FA 2 13.17% of variance (Total 27.32%)					+ Lightness_std_llf + Saturation_mean_llf + sky_ss + canny_edge_llf + + + green_other_ic + + + tree_ss + + + nature	- - - built_ss - - built_other_ic - - slum_ic - - market_ic - Hue_std_llf - street_ss - others_ss - traffic_light_od	Seems to continue the trend from the first one, with a greater focus on nature. Tracks same spectrum, but low end is highly urbanized space rather than open highway space.	Urbanness
FA 3 8.71% of variance (Total 36.02%)					+ market_ic + nature + canny_edge_llf + sky_ss + Lightness_std_llf + + no_of_blobs_llf + + Hue_mean_llf + + + Saturation_std_llf + + + Saturation_mean_llf	- Hue_std_llf - street_ss	Clarity of image, brightness of sky, and greyness/dullness of scene all seem to be reflected. Spectrum from clear, colorful, and bright to blurry, dull, and grey.	Clarity
FA 4 6.19% of variance (Total 42.21%)					+ + + person_od + + + motorcycle_od + + + bicycle_od + + market_ic + + no_of_blobs_llf + + Hue_std_llf + canny_edge_llf + slum_ic	- car_od - green_other_ic	One-way spectrum looking for people, bikes, and motos. Low end is just pictures that have nothing even mildly resembling any of these things, high end is very busy spaces with lots of people and small transport options. Markets also track highly here, because these spaces are busy with these things. Very low scores also seem to involve lots of walls and non-street spaces	Business
FA 5 6.14% of variance (Total 48.35%)					+ built_other_ic + slum_ic + Hue_mean_llf + Saturation_mean_llf + sky_ss + nature + + canny_edge_llf + + + others_ss	- - - street_ss	Unclear. Slight trend towards images with people walking around in tight spaces to open areas with cars, regardless of nature (as opposed to FA 1 and 2.) However, several images on both ends break this trend, and when looking at the inputs, its clear that "canny edge, others_SS" matter a lot, and street_ss is negative. These translate to images with many edges, little paved space, and lots of signage/words/other categories.	Complexity
FA 6 5.64% of variance (Total 53.99%)					+ + + car_od + + + others_ss + + Hue_mean_llf + truck_od + street_ss + traffic_light_od	- bus_od - built_ss - green_other_ic - no_of_blobs_llf - built_other_ic - sky_ss - slum_ic - canny_edge_llf - - nature	Extremely self-explanatory: presence of traffic, particularly car traffic and not trucks/buses/motos/bikes/ people.	Traffic Level
FA 7 5.42% of variance (Total 59.41%)					+ nature + market_ic + Saturation_std_llf + built_other_ic + + tree_ss + + + Lightness_std_llf	- - - Lightness_mean_llf - Hue_mean_llf - street_ss - canny_edge_llf - others_ss	Again, seemingly self-explanatory: brightness of image, weather, day/ night	Brightness
FA 8 4.41% of variance (Total 63.81%)					+ + + bus_od + + + truck_od + + Hue_std_llf + Lightness_std_llf + Lightness_mean_llf + others_ss	- Hue_mean_llf - green_other_ic	Presence of large vehicles, regardless of what else is going on. Note that pedestrians, bikes, cars, and motos are unrelated to scoring of this factor.	LV (Large Vehicle) Presence
FA 9 4.34% of variance (Total 68.15%)					+ + + built_other_ic + + traffic_light_od +bus_od + car_od + Hue_mean_llf + no_of_blobs_llf	- Saturation_std_llf - canny_edge_llf - motorcycle_od - others_ss - truck_od - Hue_std_llf - - market_ic - - - slum_ic	Track slums/informality, with low ratings associated with slums. Note that Montreal's lowest ratings were nowhere near the lowest for Pune, so some of those associated with it in Montreal are not strong as Montreal has little informality (for example, snowy grey alleys are marked as slightly informal)	Informality

Table 3: A chart of our 9 factors, along with interpretation. Note that the strength of the variables going into them is indicated by the +/- signs next to the variables in their columns. One sign (+/-) has a FA regression result between 0.1 and 0.25, two signs (+ +/ - -) is within 0.25 to 0.5 in value, and three signs (+++,- - -) has a value greater than 0.5.

Note that each of the 9 categories are highly complex and contain many components. It is clear that greenery seems to be a strong influence within several of the different factors, as does the technical measurements of image composition. The first two components account for more than a quarter of all variation, and are thus the most important - and the most elusive. They both operate on a spectrum from pedestrian space to car-oriented space, but the extreme urban end of the first is represented by open highways and the second by high rises and dense buildings. Both incorporate nature greatly, meaning that when it comes to evaluating a streetscape, greenery, trees, and sky are an essential part of what a computer and a human eye are analyzing. This first category highlights edges, blobs, and greenery, but has negative results for the percentage of an image that is sky or the color of an image, indicating car-centric highways and sidewalks along open roads will score lower (Yin & Wang, 2016b). This component is potentially the most useful one as it tracks so closely with many of the aspects of a streetscape that are heavily associated with walkability - high scores seem to be associated with the exact sorts of places that urbanists often highlight as typically walkable. The second follows a similar trend, with more of a focus on urban density rather than paved openness. Together, they are measuring a combination of urbanness, greenspace, and pedestrianized space - key attributes in understanding walkability.

Further down the stack, the components grow more self-explanatory. The third tracks values associated with image quality and composition, and the fourth clearly tracks bike and pedestrian activity as opposed to cars. The sixth and eighth both track different types of vehicles, car traffic and large vehicle traffic respectively. The fifth is the only category which is uncertain, as an examination of the results shows many patterns, and is heavily dependent on the influence of the segmentation result that picked up “other_ss” - elements not evaluated by other segmentation results. Because of this incoherence, the fifth result was mostly discounted. The seventh indicates brightness, regardless of other details. Finally, the ninth is clearly an inverse of informality - in which areas that resemble informal settlements will score low and formalized settlements will score high. It's worth noting that for this category Pune scored far lower, and most very low value images (slums) were found in Pune.

3.3. Results

3.3.1 Correlation patterns across users

The inter-relationship between the different user ratings using correlational analysis was examined. In general, there were high levels of correlation across all six of the user-defined walkability attributes. This means that, regardless of the attribute being measured, the values of any of them reflect an overall holistic understanding of walkability. This correlation is slightly higher for Montreal users than it is for Pune users, indicating Montreal users tend to rate streetscapes similarly in all categories more so than Pune users. This pattern can be seen here in table 4.

Bins ->	Montreal Participants 1840 Unique Images from 4128 Observations						Pune Participants 1386 Unique Images from 2774 Oservations					
Averages per category ->	3.11676357	3.338905039	3.08575581	2.76356589	3.10489341	3.05741279	2.90194665	3.176470588	3.05443403	2.97152127	2.91744773	2.87166547
Correlation Attributes	Average of RdSafe	Average of CmSafe	Average of Navig	Average of Beaut	Average of Welcm	Average of Walkbl	Average of RdSafe	Average of CmSafe	Average of Navig	Average of Beaut	Average of Welcm	Average of Walkbl
Average of CmSafe	0.596						0.493					
Average of Navig	0.855	0.591					0.667	0.579				
Average of Beaut	0.568	0.521	0.607				0.561	0.504	0.628			
Average of Welcm	0.803	0.669	0.823	0.688			0.631	0.595	0.687	0.738		
Average of Walkbl	0.879	0.567	0.888	0.612	0.856		0.770	0.517	0.760	0.668	0.748	

Table 4: Correlation Statistics across the 6 user-derived attributes, by location

3.3.2 Results - Trends in user identity

When reviewing the trends that emerge from how participant groups relate to the statistical data, a few major patterns emerge. Most significantly, picture location is a far stronger predictor for walkability values than user location, and Montreal generally ranks higher for all user-derived scoring than Pune. This is confirmed in two different ways, both through summary statistics on average values of different groups and through regression models. Figure 5 shows the averages across all groups. This demonstrates that for all ratings, it can generally be said that all users, irrespective of geographic location, agree Pune is less walkable than Montreal, and that users from Montreal tend to assign slightly (by a very small margin) better ratings for all categories. The only item which diverges from this trend is ratings of beauty, a trend which could perhaps be attributed to a “grass is always greener” effect, as participants are perhaps perceiving less familiar environments as more beautiful than environments they are familiar with.

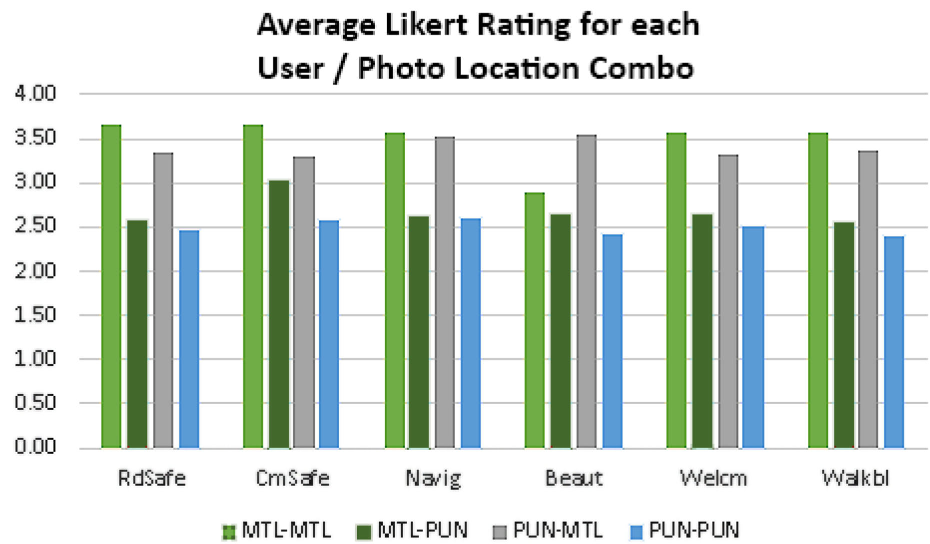


Figure 5: Trends in average user ratings by location

The strength of this pattern is demonstrated in the values of the regression model that included both location (user and image) variables, in which the values associated with picture location provided far stronger correlation coefficients than those associated with user location. This indicates that what variation is coming from user location is not especially strong compared with other physical factors affecting walkability, as location has stronger values within a regression model containing all user identity factors as possible variables. Each of these factors, besides formative environment, are 0-1 dummy variables - with “1” representing “Pune” and “0” representing Montreal for the two locational categories, and “Female” for the gender identity category. This means that the generally more negative values associated with the picture location indicate that stronger, lower walkability ratings are associated with images of Pune - and that the inverse is true for Montreal. This can be seen below in Figure 6.

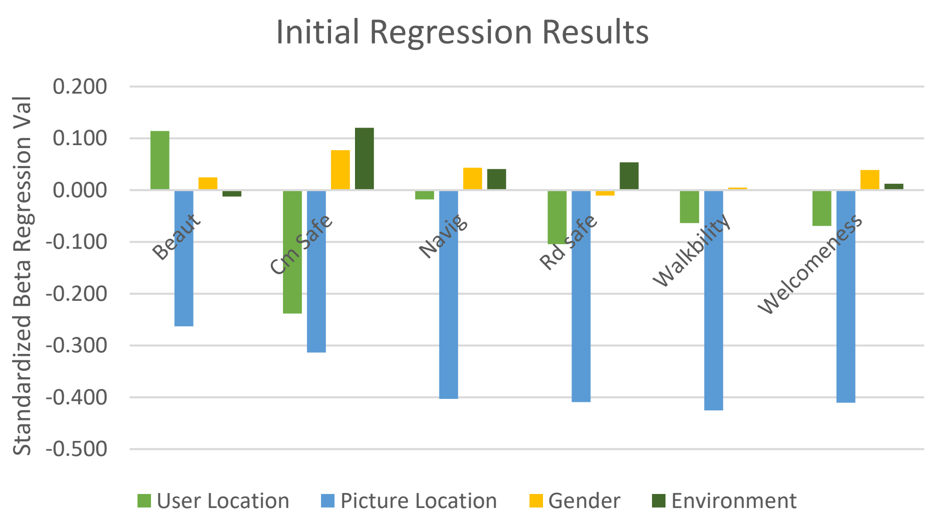


Figure 6: Regression Std Beta results for a model that contained all components and user identity factors, with a focus on the regression results for the user identity categories. User ratings for imagery were the dependent variables.

The other identity measurements, i.e., gender and user formative location (environment), did not have especially strong effects on the model. Formative environment was on an ordinal scale, with 1 (Rural), 2 (Suburban), 3 (Urban). This translates to higher environmental scores in the regression model, theoretically indicating that formative location had a stronger impact on perceptions of walkability. The only points where their impact was especially noticeable was in the crime safety and (to a lesser extent) navigability categories, which demonstrated a minor trend towards female-identified users from more built up areas giving more intensely negative crime safety ratings. Road safety on the other hand showed no gender patterns but a trend towards higher environmental scores being associated with a more positive perception of road safety in all situations - which is expected as urban users are probably more used to navigating through traffic as a pedestrian.

3.3.3. Regression Results

The regressions did illuminate some significant differences. A chart of the differences in standardized beta values, which reflect how strongly related a dependent and independent variable are, reveals which metrics showed the strongest variation between the two groups (Figure 7). Standardized beta values were chosen as the final statistic for comparison, as the values going into the factor analysis came from variables with a variety of different units, meaning to compare their relative affect against each other they must be standardized (IBM SPSS, 2022). These vary across all nine factors, and generally decrease as the factors account for less of the variation in the set. There seems to be limited regularity between the two groups, except in the fifth category, which had incoherent results as shown in the factor analysis.

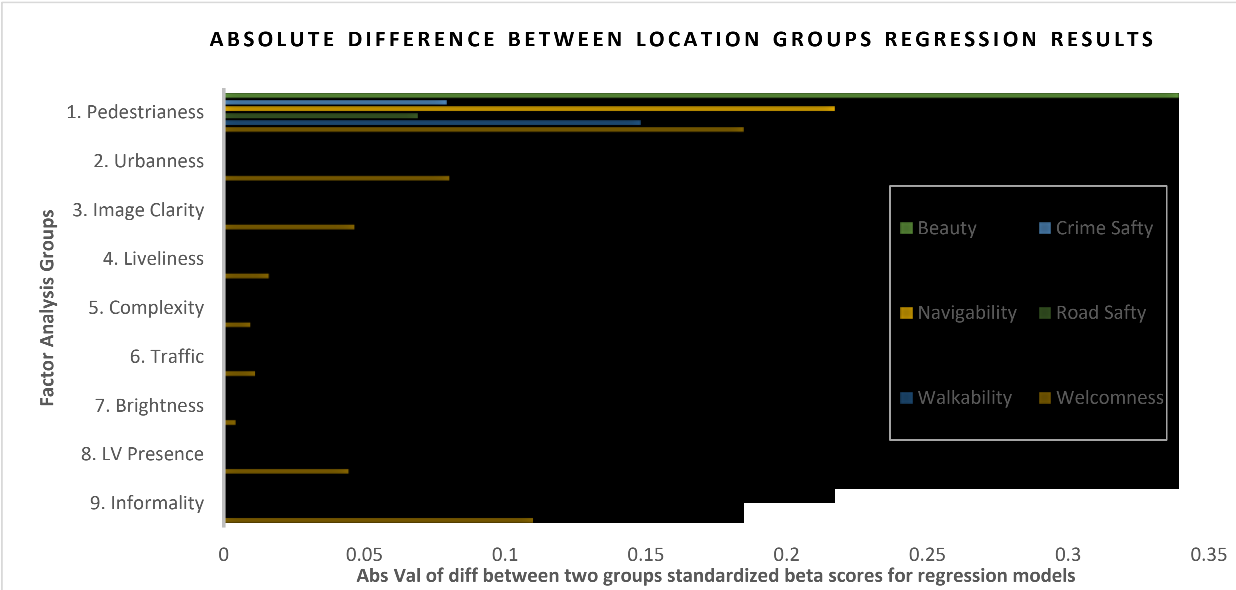


Figure 7: Bar plot of the difference between the two groups regression standardized beta values.

These patterns can be better understood through an examination of all of the standardized betas that resulted from the regressions. Significance is not evenly distributed across the factors in question, showing that different factors feed into the two groups perceptions of walkable attributes. Notably, this indicates that almost all of the seventh factor is insignificant for both bins of users. The charts below also track this, with insignificant bars not included.

Loc	MTL	PUN	MTL	PUN	MTL	PUN	MTL	PUN	MTL	PUN	MTL	PUN
Dep. Var	Beauty	Beauty	Crime Safty	Crime Safty	Navig	Navig	Road Safe	Road Safe	Walkbility	Walkbility	Welcmnss	Welcmnss
Adj. R^2	0.18642783	0.23725529	0.06202742	0.08690137	0.1264707	0.12206762	0.13504567	0.13254968	0.13403556	0.14901273	0.12139557	0.13150915

Figure 8: Charts of the standardized beta values for all 9 FA results regressions against user-ratings, with non-significant values removed. Note that size of the bar indicates intensity of opinion, and directionality indicates directionality of opinion. For example, the strongly negative value for beauty for Pune users in FA 8 indicates that they rate things with lower scores for this factor (LV) with lower beauty ratings. Also note that beauty values had the highest Adj R2 values.

These results can be used to interpret how participants from Montreal and Pune perceive urban spaces differently. Notably, some factors (3 [Clarity], 4 [Liveliness], and 9 [Informality]) show a very similar pattern in intensity between the two groups, indicating that their perception of space is in some way similar. Some (5 [Complexity] and 8 [Large Vehicles]) show moderate variation, and crucially some of the most significant factors (1 [Pedestrianness], 2 [Urbanness], 6 [Traffic], 7 [Brightness]) show extreme differences between the two. Magnitude across all categories varies greatly, and there is no consistent trend towards one group having a higher variation than others. Directionality also varies, with those that are consistently similar all possessing the same directionality - for example, all users mostly agree that high values for picture clarity are associated with higher values for streetscape ratings.

The strongest differences are in the first two categories, which account for the largest percentage of the variation in the images, accounting for nearly 30% of all image-to-image variation together. Particularly noticeable is the high positive values in the first category for Montreal users and the low values for Pune users in the same category. This indicates that Montreal users tend to rate pedestrianized greenspace images as highly walkable and wide open roadways as extremely unwalkable. Pune users, on the other hand, may see roadways in a less negative light and pedestrianized greenspaces more neutrally. In the second category, the two groups seem to agree, mostly, although Pune users demonstrate slightly stronger opinions - for Pune, buildings make areas much less walkable in all 6 rating categories. The same pattern holds true for the third and fourth, which reflect the fact that better images and a lively streetscape make an image perceived as more walkable, although user location is relatively unimportant in this case. 5, the “incomprehensible” category, has similar results and is thus essentially unimportant to this research. Traffic and brightness both affect participants' opinions in opposite ways, but are of low statistical significance. Stronger variation appears again in the last two categories, with Montreal users feeling that large vehicles make an area less walkable than Pune users, and Pune users feeling that informality makes an area more walkable than Montreal users.

Regarding how these results are distributed across the examined six aspects of walkability, interesting patterns of variation arise. Ratings of beauty tend to have by far the strongest differences between the two groups' perceptions, indicating that the conceptualization of environmental beauty seems to vary between cultures - this is corroborated by literature (Hull & Reveli, 1989), and by the aforementioned summary statistics. Crime also has a high amount of variation, with most of the other values having less well-defined patterns. The catch-all metric, “walkability”, has a slight tendency to track with the ratings assigned to welcomeness. Figure 5 above shows the average total variation between the two for each of the rating categories, and highlights the “beauty” category’s outsize impact.

A few additional details within the regressions plot are worth drawing attention to. These include the generally weak values for road safety. Navigability was not significant for Pune users in the first category (complexity), despite being significant for Montreal users. It is notable that vegetation and greenery are major components of several of the most varied factors, indicating that the differences in perception between the two groups may partially be rooted in different opinions of how greenspace affects streetscapes.

3.3.4 Uncombined variables regression results

These results can be confirmed by looking at a regression of the two user groups independently, without the factor analysis simplified results. This table shows the same patterns, in which Pune users value greenery more, both have slightly different opinions about certain key features, and most things related to picture quality, pedestrians, and informality are similar. Montreal users' strong valuation of “canny edge” is particularly noticeable, as this metric reflects how many edges are in the image and thus perhaps how complex the image is. Also noticeable here is the average lower ratings coming from Pune users, which indicate that they have a general feeling that fewer spaces are walkable than Montreal users do.

	Montreal Participants						Pune Participants					
Segmentation Values	Average of RdSafe	Average of CmSafe	Average of Navig	Average of Beaut	Average of Welcm	Average of Walkbl	Average of RdSafe	Average of CmSafe	Average of Navig	Average of Beaut	Average of Welcm	Average of Walkbl
built_other_ic	0.1290	0.1260	0.1390	0.0900	0.1110	0.1280	0.0829	0.1036	0.0998	0.0820	0.0969	0.1051
green_other_ic	0.1450	0.0360	0.1400	0.2830	0.1450	0.1460	0.1531	-0.0718	0.0267	0.2293	0.1002	0.1223
tree_ss	0.0310	-0.0580	0.0480	0.2520	0.0760	0.0610	0.0751	-0.0037	0.0111	0.0682	0.0770	0.0899
street_ss	0.0230	-0.0490	0.0140	-0.0990	-0.0160	0.0260	-0.0897	-0.0978	-0.1027	-0.2344	-0.1626	-0.1010
built_ss	-0.0030	0.0090	-0.0260	0.1600	0.0060	-0.0270	0.1172	0.0404	0.0661	0.2511	0.1518	0.1071
Saturation_mean_llf	-0.0550	0.0850	-0.0800	-0.0990	-0.0480	-0.0980	-0.0189	0.1406	0.1088	0.1813	0.0993	0.0258
Lightness_std_llf	0.0960	0.1110	0.0810	0.1480	0.1120	0.0750	0.1457	0.1254	0.1405	0.2120	0.1770	0.1531
Saturation_std_llf	-0.1050	-0.0670	-0.0920	-0.0090	-0.1000	-0.1040	-0.0913	0.0578	0.0029	-0.0442	-0.0112	-0.0281
canny_edge_llf	0.1380	0.0170	0.1480	0.3050	0.1750	0.1890	0.1207	-0.0658	-0.0527	0.0145	0.0551	0.0668
no_of_blobs_llf	0.0680	0.0370	0.0900	0.2340	0.1270	0.1200	0.0940	0.0286	0.0372	0.0121	0.1107	0.0896
market_ic	-0.0140	-0.0250	0.0110	0.0110	0.0120	0.0230	-0.1178	-0.0816	-0.1292	-0.1591	-0.0850	-0.1088
bicycle_od	-0.0750	-0.0570	-0.0490	-0.0100	-0.0490	-0.0500	-0.0541	-0.0474	-0.0409	-0.0660	-0.0395	-0.0514
motorcycle_od	-0.2390	-0.1760	-0.1880	-0.0760	-0.1840	-0.1880	-0.2546	-0.1781	-0.2380	-0.3141	-0.2273	-0.2764
person_od	-0.1940	-0.1520	-0.1470	-0.0420	-0.1350	-0.1390	-0.1955	-0.1006	-0.1677	-0.2730	-0.1691	-0.1985
slum_ic	-0.1880	-0.2140	-0.1630	-0.2080	-0.1880	-0.1450	-0.2197	-0.2792	-0.2663	-0.3543	-0.3210	-0.2461
bus_od	-0.0960	-0.0460	-0.1040	-0.0980	-0.1050	-0.1130	-0.0929	-0.0108	-0.0849	-0.1194	-0.0749	-0.0948
car_od	0.0960	0.1390	0.0720	-0.0830	0.0960	0.0700	0.0468	0.1811	0.1574	0.1112	0.1195	0.0989
traffic_light_od	0.0370	0.0500	0.0380	-0.0830	0.0340	0.0120	0.0222	0.0948	0.0984	0.0643	0.0450	0.0624
truck_od	-0.1980	-0.0870	-0.2100	-0.1830	-0.1880	-0.2190	-0.2119	-0.0664	-0.1676	-0.2445	-0.1670	-0.2252
Hue_std_llf	-0.0130	-0.0830	0.0150	0.0770	0.0180	0.0380	-0.1250	-0.1388	-0.2043	-0.2657	-0.1770	-0.1621
Lightness_mean_llf	-0.0440	0.0500	-0.0530	-0.1450	-0.0420	-0.0640	-0.0326	0.0274	-0.0104	0.0246	-0.0161	-0.0690
sky_ss	0.0370	0.0390	0.0890	-0.0310	0.0630	0.0770	0.0032	0.0712	0.1004	-0.0071	0.0349	0.0777
nature	-0.0670	0.0020	-0.0780	-0.1130	-0.0640	-0.0780	-0.0815	-0.0230	-0.0881	-0.1105	-0.0833	-0.1305

Figure 9: Standardized beta results for binned regression models against all variables that were components of factors

Generally, Pune users have ratings for these categories that come closer to a central value. This means that the opinions of Pune users, when compared with the opinions of Montreal users, tend to be less strong. This may be somehow related to Montreal users having a weaker background knowledge of urban studies, with the average familiarity rating of students in Pune a point higher (Ave 4.5/10 Pune, 3.5/10 MTL) than users from MTL. The exception to this pattern is Pune users rating of beauty, which plays a far more important role in most of the categories ratings than it does for Montreal users. This pattern is also supported by the high adjusted r-square for the Pune beauty regression shown above.

3.4. Discussion

Our results do indicate that there is a difference in the two groups' perception of walkability, thus answering the original research question. It is clear, as shown in figure 8, that in several key categories (particularly the first two factors, pedestrianness and urbanness) users from Pune and Montreal disagree. This disagreement is also shown in the average ratings, within which users from Montreal consistently have stronger ratings across all 6 user-defined categories.

Especially noticeable in this difference is the strong variation in perception of beauty. Beauty is statistically significant in all 9 factors, and has the largest differences between the two groups in every single metric explored. Previous research has often noted the intercultural differences of conceptualizations of environmental beauty, which makes this result all the more compelling (Hull & Reveli, 1989.) This difference is most noticeable in factors 1,4,6, and 9 - all of which can be understood to be classical components of urbanist definitions of walkability. There is also mild variation between the two groups present for two additional identity measurements, gender and formative location. Although this variation was not particularly significant, it does indicate that there are differing patterns to how we perceive urban space that can be generalized across populations.

Drilling into the milieu of this specific cross-cultural comparison, the question of the compatibility of these two groups arises. A few generalizations can be made, but attributing them to culture is specious. These include the importance of natural features as an indicator, which seem to affect the two groups ratings differently - all of the factors that had natural variables tended to have higher variability between the two. Complexity may be more pleasing to Montreal users, and less pleasing for Pune users. This, along with the results of the undifferentiated regressions, may imply that Pune users may have a narrower definition of walkability than Montreal users. Additional evidence for this comes from the above correlation analysis, which shows that Montrealers tend to rate streetscapes similarly across all categories more so than Pune residents. Again, there are clearly major differences in how the two groups perceive environmental beauty, as it pops up over and over as the measurement with the greatest variability between these two groups.

However, despite these differences, there is evidence that some forms of universalized walkability exist. The strong impact of picture location speaks volumes towards this. Picture location's significance tended to be far greater than that of user location, and its beta-value impact on measurements was sometimes twice or more the value of the user location. This suggests that regardless of user identity, there is something about walkability values that may transcend individual perception. In this case, these values indicated again and again that all users considered Montreal (or certain types of streetscapes that Montreal is composed of) a far more walkable place than Pune.

Universalized walkability is also apparent in the high correlation values between the 6 user-defined ratings. All showed very high levels of correlation, indicating that users tended to rate images high or low in all rating categories during the exercise. This means that a picture that is beautiful is also likely to be safe, navigable, welcome etc. This confluence implies that walkability is a measurement that incorporates within it all of these different categorical aspects of human perception of built environments - one cannot be measured without the others. This trend exists for both locations, but is slightly higher in Montreal.

Our results show two seemingly contradictory things - walkability transcends culture and identity, yet is defined differently by different groups. Taken together, these conclusions paint a confusing picture. It has been previously established that walkability is an elusive and poorly designed measurement. A cursory examination of the literature feeding into this study demonstrates a multitude of different definitions of walkability, showing that the problem outlined here has also been identified by other researchers. This incongruity implies that walkability represents a holistic measurement - something that is mostly defined by external perceptions but partially defined by internal experiences. This confusion between the two is perhaps the most significant result of this work - walkability is nebulous and confusing, and any claim otherwise is likely leaving out important details or over-simplify the concept.

Several issues cloud the ability to derive strong statements from this data. It is difficult to account for individual subjectivity in this case. Participant demographics showed a large amount of variation, with biases towards young females from urban areas. Additionally, image appearance and lighting is extremely significant in these results. This is an unfortunate but not unexpected result of the online-only format of the survey imposed by COVID-19. Lighting and blurriness was shown to have a large effect on the data, outweighing many other factors – for example, the third component, clarity, accounted for almost 10% of all variation and image quality factors were part of several other components. This issue means certain parts of this study should be interpreted with a high degree of caution, and perhaps indicates a potential systemic issue for online surveys of streetscapes as a methodology in walkability studies.

Generally, these results were not especially strong, indicating the complex nature of the subject being analyzed. Much of the literature outlined before demonstrates the weakness of the measurement of walkability itself - and it's possible the data is reflecting that. The conclusions of research critiquing walkability, when considered in the light of evidence about the subjectivity of the topic, add even more credence to the argument that the fuzziness in this data reflects a larger issue.

3.5 Conclusions

It is a challenge to interpret contradictory results such as these, but an examination of their magnitude provides clarity. It is clear that when it comes to culture, definitions of walkability vary, but this variability is only operating on a smaller perceptual scale. The general trend, when the finer details and nuances are excluded, is towards universalized walkability and understandings of the concept that transcend location and background. This conclusion is supported by the statistical analysis which showed that A) location of picture vastly outweighs user location in terms of impact on walkability rating, B) identity heavily impacts what is important to a user when rating walkability (beauty vs safety vs greenery etc. etc.), and C) identity groups tend to agree on combined walkability ratings for images even when they disagree as to how to rate specific traits of a streetscape.

This nuanced conclusion makes sense, given the limitations of cultural and environmental background on human experience - we all, on some level, have very similar needs in terms of comfort and safety. Most people can all agree that a highway filled with traffic is not a good place to walk and that a forest is more pleasant than a dark alleyway. Where we differ is in the magnitude of these opinions rather than the opinions themselves. The results of this research potentially indicate that subjective walkability is operating on a more personal scale than objective walkability. Perceptions of urban space, like quantum physics, behave differently if you observe them from a macroscopic (city-wide) scale or from a microscopic (individual) perspective.

The implications of this scalar difference for future research into walkability studies are important. Many existing studies and urban planning projects seek to develop walkability indices that are culturally and geographically appropriate for a certain context. Assuming that the paradoxical results presented here are correct, further research needs to be done to understand what aspects of walkability are more universal and which are culturally and individually subjective. Separating these two types of walkability indices can allow practitioners to design and understand built spaces that are both inclusive for the maximum number of people and locally appropriate for the populations that use them the most.

Walkability, as ever, remains a nebulous and difficult to synthesize concept. The results of many of the studies that inspired this work have reached similar conclusions, with some even implying that the subject may never be truly defined or that it is purely subjective. However, it is clear from studies like this that walkability does matter, and is both subjective and objective. Only through further research can these intertwined aspects be decoupled.

Ch. 4: Conclusions and recommendations for further research

4.1 Our Findings

A review of the evidence accrued in both the literature review and the empirical study points towards the same conclusion – walkability is fuzzy. It's fuzzy because as a concept, it has grown into an useful catch-all measurement for positive urban design traits; in short, it has become so broad that it has become incoherent. As more things have been ascribed to and derived from walkability, its ease of use as a measurement has decreased. Simultaneously, the prevailing trends in social science research, including walkability research, have sought to incorporate and evaluate the importance of identity and subjectivity. This has further destabilized the singular concept of walkability. This study further looks into this by finding that walkability is partially subjectively determined and partially an objective universalized measurement.

These trends were soundly demonstrated within the above literature review. The literature review showed that walkability is a measurement derived from many different sources, and over time has moved from a measurement solely tied into quantitative evaluations of the built environment towards evaluations that incorporate groups of people's perspectives on physical spaces. This trend coincided with walkability being increasingly used as a measurement of other traits, including such nebulous subjects as quality of life and good urban design. The term has also expanded beyond its original bounds of health research, first into urban planning and design, and now further afield into other forms of social science research. This growth has spurred its own sub-field development, with “metawalkability” research booming in the past 10 years. Numerous studies have been published that either serve to define different concepts of the term, provide exhaustive literature reviews, or unpack and critique walkability applicability.

Chapter 3’s findings complimented these trends. After evaluating how two different sociocultural groups of people perceived walkability differently, it was found that they differed in their perceptions of walkable space. These differences were stronger when it came to attributes that were more closely related with abstract feelings and aesthetic sensibilities, and weaker when it came to attributes related to physical obstacles and greenery. However, despite these differences, it was also clear that there is a stronger (than the tendency towards differing perceptions) trend towards perceiving a space as walkable or unwalkable, regardless of the details as to which attributes make it such. These two results indicated to us that the subject of walkability is complex, as it seems to be something that many people can agree upon exists, and agree that certain areas are walkable/unwalkable, but personal background may affect how that conclusion is reached without changing the final decision. This convoluted conclusion indicates the same trends that the literature review found – walkability is a broad subject that seems to work well as a measurement for many things, but is highly subjective in terms of the details as to why.

4.2 Subjectivity, walkability, and further recommendations

One of the primary conclusions of both the literature review and the empirical study is that subjectivity and identity has a role in walkability and is increasingly becoming a part of walkability research. This trend has not just been limited to walkability studies, as numerous other fields have become preoccupied with this dichotomy. This preoccupation has uprooted established directions of social science and heavily affected certain types of research. The inclusion of the role of identity in the human experience is at the heart of the recent more critical direction research has gone in, and identity-induced subjectivity is an important aspect of gender studies, race studies, and other types of research that explore the relationship between the marginalized and the mainstream (Graeber and Wengrow, 2020; Phinney & Onwughalu, 1996). It is important to note here that identity, sociocultural group, and other factors that serve to separate human experiences are nebulously defined and difficult to pin down in a quantitative manner.

Given the drastic effects subjectivity has had on other fields of study, it is likely that the increasing role it plays in walkability research will have major effects long-term on the usage of walkability as a measurement, though what these effects are is uncertain. The results contained in this thesis hint at a possible answer to this question, indicating that walkability, like quantum mechanics, operates differently at different scales of perception and detail. The inclusion of perspective and subjectivity has had an overall positive effect on social science research, as attempting to understand how a phenomenon applies in the context of any one identity or experience helps us understand the phenomenon further. However, the conclusions of studies exploring how identity intersects with walkability should not be ignored, as they have the potential to nullify previous conclusions and cross-contaminate current work.

One aspect of this trend that is particularly concerning is that the era of fuzzy walkability is occurring simultaneously as machine learning techniques are increasingly used in walkability research and applications. Machine learning techniques are popular in the analysis of streetscape imagery and data, and can be used to construct larger models of walkability with limited data – indeed, such a technique was applied in this research. However, computer vision techniques and machine learning often depend on information that is authoritative, and the processing that occurs happens within an algorithmic black box. Computer-vision derived walkability presents itself as a quantitative measurement derived from mathematical calculations, but because the term itself is uncertain and any data derived from human experience may be colored by subjectivity, the conclusions from these models may be suspect.

Taken together, these conclusions present a rich potential source for further research. This study has not successfully separated the aspects of walkability that are seemingly universal and those that are subjective – and this paper does not purport to do so. However, it is clear that there is a difference between these two. In only this limited case, it was found that aesthetic sensibilities and perceptions of safety seem to vary greatly across the two different study groups. With more data and more research, significantly broader conclusions about what makes walkable spaces universally walkable can be teased out, and what makes some spaces perfect for some groups can also be determined.

The implications of this are also worrisome for the field of walkability studies. Several studies have found that different walkability indices are not compatible with each other. Chapter 3 showed that different individuals and different groups may perceive the subject differently. Without a good understanding of what goes into universalized walkability, it is likely that researchers will continue to apply the measurement in such a way that many of the results are not comparable with each other. Furthermore, some of these results may only be applicable for a certain group or may not reflect perceptions of walkability in places beyond the context in which a particular study occurred.

This confusion is an important problem in walkability studies, and if it is not resolved soon, it can potentially undermine much of the research performed thus far in the field. An increasing body of research is showing that social science measurements, including walkability, vary subjectively. Ignoring this research and continuing to apply a wide variety of walkability measuring systems in many different contexts without further data, risks making the term inconsequential and meaningless. A standardization of walkability measurements is needed, with a focus on distinguishing which factors can be applied broadly and which are culturally variable. Perhaps this is the most significant finding of this research, as further enquiry into this issue has the potential to clarify and improve future work on walkability.

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