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Inclusive Accessibility: Integrating Heterogeneous User Mobility Perceptions into Space-Time Prisms

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Travelers' day-to-day mobility depends on their perceptions, experiences, and personal characteristics. Many accessibility measures overlook perceptual factors and mainly consider space–time limitations of mobility, overestimating travelers' potential mobility. We introduce a novel inclusive accessibility concept that advances time-geographic accessibility measures in light of travel behavior theories. We conceptualize inclusive accessibility as a subset of the classic space–time prism (STP) that incorporates hard constraints (e.g., limited infrastructure and services and time) and soft constraints (e.g., perceptions of safety and comfort toward the built environment and infrastructure and travel time preferences). We collected survey data on individual-level mobility perceptions and applied machine learning algorithms to predict personalized soft constraints for walking. Considering public transit and walking, we model and compare three network-based STPs: classic STP with hard constraints, inclusive STP with soft spatial constraints, and inclusive STP with soft spatial and temporal constraints. Our method demonstrates heterogeneities in individuals' mobility perceptions. We illustrate that the individual's level of accessibility shrinks substantially as we approach more conservative measures that include travel perceptions. Our method highlights the differences between travelers' physically and psychologically accessible space depending on their travel choices and exposure. *Key Words:* active transportation, hard and soft spatial constraints, physically and psychologically accessible space, public transit, smartphone-based mobility survey.

Travel needs, patterns, and experiences within urban settings vary across people of different age, gender, income, and life stage. Factors affecting travel behavior (e.g., attitudes, perceptions, and personal experiences) bridge the connection between these varied travel needs and actual travel (Alfonzo 2005; Singleton and Clifton 2015; Ma and Cao 2019). Depending on their attitudes and perceptions toward the built environment, people could experience different mobility barriers within the same travel environment (e.g., availability of infrastructures and opportunity locations, road surface conditions, safety, and cleanliness; Ma and Cao 2019). Individuals' day-to-day travel is a trade-off between their travel needs and perceptions of mobility constraints.

Over the years, transportation researchers have developed models predicting human travel behavior (Alfonzo 2005; Burbidge and Goulias 2009; Singleton and Clifton 2015). These theories suggest that nonautomobile travel behavior is influenced by not only physical ability, time, and monetary budget

(Alfonzo 2005; Singleton and Clifton 2015), but also mobility perceptions and experiences with the built environment (Handy, Cao, and Mokhtarian 2005; Götschi et al. 2017). Similarly, transit and active transportation usage is affected by safety perceptions, which vary by age, gender, and personal experiences (Sönmez and Graefe 1998; Spears, Houston, and Boarnet 2013; Abenoza et al. 2018). Addressing these perceptual mobility constraints through built environment changes, such as redesigning road infrastructure and restructuring land-use patterns, could influence individual attitudes toward active and transit travel and reduce car usage (Taylor et al. 2009; Tracy et al. 2011; Zhang et al. 2012; Schoner, Cao, and Levinson 2015; Aziz et al. 2018; De Vos, Ettema, and Witlox 2018; Rahman and Sciara 2022). Despite its significance, few studies demonstrate the applications of individual-level behavioral aspects in designing multimodal transportation systems, including transit, biking, and walking. One of the reasons for this limitation is the

tedious nature of capturing the intricate details of human travel behavior and its underlying heterogeneity.

Person-based accessibility measures account for the spatiotemporal complexities involved in human mobility (Miller 2017); thus, it offers an effective framework to incorporate heterogeneous travel perceptions in accessibility. Person-based accessibility measures quantify a person's ability to reach essential services and opportunity locations (e.g., jobs, health care, and green space) from key locations (e.g., home, work, or a neighborhood), based on scheduling constraints imposed by required activities that are fixed in space and time (Levinson and Wu 2020). Such measures typically adopt the concepts of time geography, including the ability to trade time for space in movement (Hagerstrand 1970; Kim and Kwan 2003). In other words, time geography assumes that people get longer activity participation time at a location if they travel shorter and vice versa. Person-based accessibility uses this time-geographic concept of space-time budgeting to identify a person's potential course of action. Past studies have developed extensions of person-based space-time accessibility measures to capture constraints such as network and non-network barriers and costs (Neutens et al. 2008; Miller and Bridwell 2009; Lee and Miller 2019).

Although powerful, the classic person-based accessibility measures are physicalist in nature (Thrift 1977) and limited in capturing diverse travel perceptions and their influences on actual travel (van der Vlugt, Curl, and Wittowsky 2019; J. Ryan and Pereira 2021). Due to this neglect of the implicit barriers or frictions experienced by people with different socioeconomic backgrounds, these measures can overestimate accessibility by preventing the physical accessibility limits expressed by space-time measures from being fully realized. For example, previous research indicates clear gender and age differences in perceived safety and comfort levels in walking and biking through different built environments and street designs (Yavuz and Welch 2010; Delbosc and Currie 2012; Le et al. 2019). This can introduce biases in accessibility measures for some social groups and travel episodes that are overlooked by classic space-time measures (Kwan 1999).

This study introduces concepts and measures of inclusive accessibility to address the limitations of classic access. Inclusive accessibility reflects

heterogeneous travel perceptions that can vary across individuals and social groups. Inclusive access is an attenuated version of classic access that considers both physical and perceptual travel constraints. Where classic accessibility estimates potential mobility based on physical space-time limits only, inclusive accessibility also incorporates perceptions that can attenuate physical accessibility. The shift from classic to inclusive measures allows planners and policymakers to understand equity and fairness in locating transportation infrastructure and essential services that are likely to vary across different population groups with diverse financial and physical abilities, risk perceptions, and acceptance.

The inclusive accessibility concept categorizes accessibility constraints into hard and soft constraints. *Hard constraints* capture the physical space-time limitations toward travel (e.g., travel time budget, location of fixed activities, and activity duration), whereas *soft constraints* are personal perceptions toward the land-use-transportation environment and time. We develop a person-based inclusive accessibility measure that accounts for hard and soft constraints using time-geography concepts and machine learning (ML) techniques. The objectives of this article are first, to formulate an individual-level inclusive accessibility measure integrating both hard and soft constraints, and second, to exemplify the variations in inclusive accessibility across travelers using case studies from a mobility survey. This study focuses on measuring inclusive accessibility considering public transit and walking only, although it applies to other travel modes.

The article makes several contributions. It is the first to develop a person-based accessibility measure that incorporates the perceptions and attitudinal factors as soft constraints, therefore making the prior physicalist measures more realistic. In addition, we curate a novel data collection approach for capturing individual-level mobility perceptions and use ML algorithms to quantify individual-level soft constraints from the data set. Policymakers and practitioners can adopt similar data collection approaches on a larger scale for the real-life implementation of this study.

The rest of the article is structured as follows. The "Background" section summarizes the past literature on travel behavior and accessibility to highlight the research gap and the importance of this study. We then discuss the conceptual framework of

inclusive accessibility. The “Data” and “Method” sections describe, respectively, data requirements and model criteria. We then present findings from case studies demonstrating the application of the inclusive accessibility concept in measuring person-based accessibility. In the “Discussion” section, we assess the merits, limitations, and future potentials of our concept, and we conclude the article by outlining future research directions.

Background

In this section, we summarize travel behavior research demonstrating the influences of spatiotemporal, built-environment, and socioeconomic factors on human travel behavior and its variations across social groups. Next, we discuss the criteria and methods used in the past person-based accessibility measures. Finally, we overview the current studies that underscore the differences between accessibility measures with and without considering mobility perceptions.

Social Differences in Travel Behavior and Mode Choices

Travel behavior research underscores the influences of personal behavior (e.g., choice, perception, habit, attitude) and sociodemographics in characterizing human travel and activities (Burbidge and Goulias 2009; Van Acker, Van Wee, and Witlox 2010; Goulias 2018). In particular, this research suggests that personal preferences toward the built environment (e.g., network and land use) play an essential role in travelers’ travel decisions and choices for active transportation (Singleton and Clifton 2015; Götschi et al. 2017). For instance, people generally prefer walking or biking on complete and connected pedestrian–bike infrastructures (Howard and Burns 2001; Khatri et al. 2016). In contrast, other street characteristics, including mixed-traffic lanes, higher speed, heavy traffic volume, a higher number of intersections and traffic signals, and on-street parking, are the primary reasons behind the current lack of interest in active travel among people (Sener, Eluru, and Bhat 2009; Khatri et al. 2016; Le et al. 2019).

Safety perception developed through personal sense of places and past travel experiences is another major determinant of travelers’ mode choice decisions. Travelers prefer to walk and bike more in their

familiar neighborhoods and routes, considering them safe, walkable, or bike-friendly regardless of their network type and road characteristics (Howard and Burns 2001; Voorhees et al. 2010). Also, experienced and frequent transit and bike riders are often less concerned about these safety issues than others (Sener, Eluru, and Bhat 2009; Delbosc and Currie 2012).

Additionally, people’s willingness and time preferences for multimodal travel vary by their trip purposes and overall travel attitudes. As opposed to car travel, transit, biking, and walking are less preferred for work travel as individuals often perceive these modes as time-consuming, stressful, and unsafe (Heinen and Bohte 2014; Li, Huang, and Axhausen 2020; McKenzie 2014; Young, Allen, and Farber 2020). In fact, low-income populations often choose car travel over other inexpensive travel options to save travel time and increase activity participation opportunities (Ettema et al. 2010; Blumenberg 2017).

Finally, travelers tend to make trade-offs between these perceptual factors in their daily mode choice decisions, depending on their age, gender, income levels, life stage, and personal experiences (Alfonzo 2005; Singleton and Clifton 2015; Ma and Cao 2019). For instance, women, children, and older adults are generally more concerned about personal well-being and security related to crime and other harassment during public transit rides or active travel at certain times of the day, such as evening or night hours (Yavuz and Welch 2010; Delbosc and Currie 2012; Le et al. 2019). Choices to ride transit also differ within social groups based on their residential locations in urban and suburban areas and the availability of transit services (Mercado et al. 2012; Paez et al. 2010). Likewise, older adults, despite being the group most interested in walking, consider themselves more vulnerable than others due to the lack of proper pedestrian facilities and higher risks of crashes and injuries (Lachapelle and Cloutier 2017; Arranz-López et al. 2019). This study aims to capture these diverse mobility perceptions and their influences on travelers’ potential mobility across individuals and social groups.

Space–Time Accessibility Measures

Accessibility refers to the ability to reach activities and opportunities (Levinson and Wu 2020). Accessibility measures are broadly classified into two categories: place-based (or location-based) and

person-based (or individual-based; Geurs and Van Wee 2004). Place-based measures quantify the proximity of facilities from the origin based on distance or travel time (Levinson and Wu 2020). Place-based measures are typically static and generalized concepts and cannot address the dynamic and individualistic nature of human travel behavior and traffic conditions (Miller 2005). In contrast, the person-based accessibility measure highlights the time-varying nature of human travel and activity across space. Specifically, these measures represent the opportunities or services accessible by individuals from their origin, considering their personal activity pattern and their scheduling and coordination with the built environment (e.g., land use and transportation; Kwan 1998). In addition, person-based accessibility measures can accommodate an individual’s physical, social, and economic constraints to travel. This method is appreciated for its microlevel analytical approach to studying intricate human travel behavior patterns.

Time geography theory conceptualizes time and space as limited resources and analyzes the space–time allocations of humans to determine their potential course of action within their surrounding physical environment (Hagerstrand 1970; Thrift 1977). The most common quantification approaches to person-based accessibility are time-geography-based space–time prism (STP) and potential path area (PPA). STP is a three-dimensional construct representing accessibility in geographic space with respect to time, constrained by anchors such as a fixed origin, fixed destination, or a fixed origin–destination pair. Based on these anchor locations and times, a person can participate in activities subject to his or her time budget and other constraints, including the speed limits afforded by different transportation modes (Kim and Kwan 2003; Miller 2005; Neutens et al. 2008). STP contains two parts: forward cones and backward cones. The forward cones identify all space–time locations reachable from the origin within a travel time budget. Conversely, the backward cone captures all space–time locations from where an individual could arrive at the destination within the same travel time budget (Delafontaine, Neutens, and Van de Weghe 2011). Finally, the STP measure is a subset of the space–time points in the forward and backward cone where a traveler can start from the origin, reach a flexible activity

location, and stay at least for the minimum activity participation time, then arrive at the destination within a time budget.

The PPA is the projection of STP to geographic space. A PPA contains all locations that can be reached between two fixed activity locations and times using a fixed travel time budget and other costs (Kim and Kwan 2003; Miller 2017). Figure 1 illustrates PPA derived from a general STP. The gray area on the horizontal x -axis presents the PPA between point locations x_i and x_j , considering the travel time window t_{ij} and minimum activity participation time a_{ij} (Miller 2005).

Recent decades have seen many extensions and elaborations of the classic STPs. These studies mainly focus on a better representation of the physical travel environment, strategies for dealing with nonuniform time-varying network properties (e.g., travel velocity, traffic volume, and congestion), and consequent travel uncertainties. For instance, the network time prism captures variable travel speeds along static or dynamic transportation networks (Miller 2008; Neutens et al. 2008). Other network-based STP measures, such as robust prism and reliable STP, are stochastic and quantify uncertainties and travel delays (Chen et al. 2013; Song and Miller 2014; Song et al. 2016; Lee and Miller 2020). These network-based STP measures are often presented as a two-dimensional potential network area (PNA), illustrating the network space accessible to a person based on his or her activity locations, time budget, and other network properties (Miller 2008).

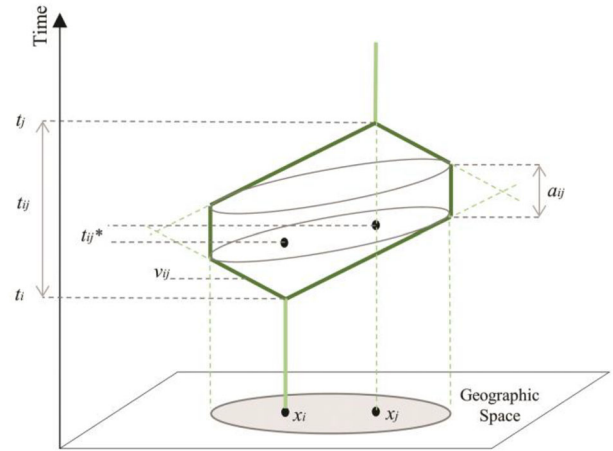


Figure 1. Space–time prism and associated potential path area. Based on Miller (2005).

Other non-network elements of the built and natural environment (e.g., elevation, water bodies, buildings, and restricted areas) often cause similar impedance to movement in accessibility, captured in some STP extensions, namely field-based prism and rough prism (Miller and Bridwell 2009; Delafontaine, Neutens, and Van de Weghe 2011; Liu, Yan, and Chow 2015). As indicated, these past STP measures are mainly physicalist and only consider the spatiotemporal limitations of human travel and activity participation. In most cases, existing accessibility measures overlook perceived constraints that might affect people's potential to reach their destinations.

Perception-Based Accessibility Measures

Past literature contains very few studies that acknowledge the limitations of physicalist space-time accessibility measures. Most studies follow a qualitative geographic information systems (GIS)-based mixed-method approach initiated by feminist geographers to embed gendered experiences and social and behavioral theories within the positivist and empiricist framework of GIS (Kwan and Knigge 2006; Cope and Elwood 2009). Some pioneering work includes STP measures by Kwan and Hong (1998), where they overlaid individuals' PPAs with the opportunities located in their preferred or familiar areas, rated by the participants on a gridded map. In another study, Kwan (1999) underscored the underlying gender biases in STP measures as women participate more in multipurpose travel in their daily life, adding higher levels of space-time constraints in terms of their access to urban opportunities. Other similar studies also analyze qualitative information (e.g., narratives and sketch maps from interviews and focus group discussions) using geospatial tools to explain the impacts of gendered and life experiences of individuals on daily mobility and accessibility (Kwan and Ding 2008; Boschmann 2011; Mennis, Mason, and Cao 2013; Tiznado-Aitken et al. 2020). Although effective, the data collection approaches adopted in these studies are quite time-consuming and do not support the quantitative analysis required to integrate travel perceptions into classic STP measures.

A few recent studies have coined the term *perceived accessibility*, which refers to the apparent ease of reaching opportunity locations using the available

urban transportation system (Cheng and Chen 2015; Lättman, Olsson, and Friman 2016, 2018; Ryan et al. 2016; van der Vlugt, Curl, and Wittowsky 2019; Pot, van Wee, and Tillema 2021). These studies categorize accessibility constraints into two parts: objective and subjective measures. The objective measures are the space-time limitations considered in the past accessibility literature. On the other hand, the subjective measures are the perception-based factors that contribute to an individual's travel decisions and mode choices, such as mode preferences by activity type (Lättman, Olsson, and Friman 2016, 2018; Ma and Cao 2019), perceived ability to reach activities using transit and walking (Cheng and Chen 2015; Ryan et al. 2016; J. Ryan and Pereira 2021), and overall perception of time and built environment as an outcome of human cognitive processes (Ma and Cao 2019; Pot, van Wee, and Tillema 2021). Regardless of the diverse considerations of subjective measures, these studies underscore that accessibility using objective measures causes overestimation compared to perceived accessibility (Gebel et al. 2011; Lättman, Olsson, and Friman 2016, 2018; Ma and Cao 2019; J. Ryan and Pereira 2021). These studies also point out the differences in accessibility by age, gender, lifestyle, and residential locations (Cheng and Chen 2015; Tiznado-Aitken et al. 2020). Most of the past research on perceived access is measured at an aggregate level that might be ineffective in preserving the distinctive nature of travel perceptions.

Conceptual Framework

Inclusive accessibility is an STP measure considering a person's physical and perceptual ability to reach activity locations. The inclusive STP is a modification of classic STP that contextualizes an individual's space-time limitations of travel along with his or her perceived mobility barriers. To accomplish these properties, the inclusive STP categorizes accessibility constraints into hard and soft constraints. Figure 2 provides a general framework of the inclusive accessibility approach used in this study.

Hard and Soft Constraints

Hard constraints refer to the physical and objective constraints that a traveler must fulfill to travel and participate in activities. These constraints are

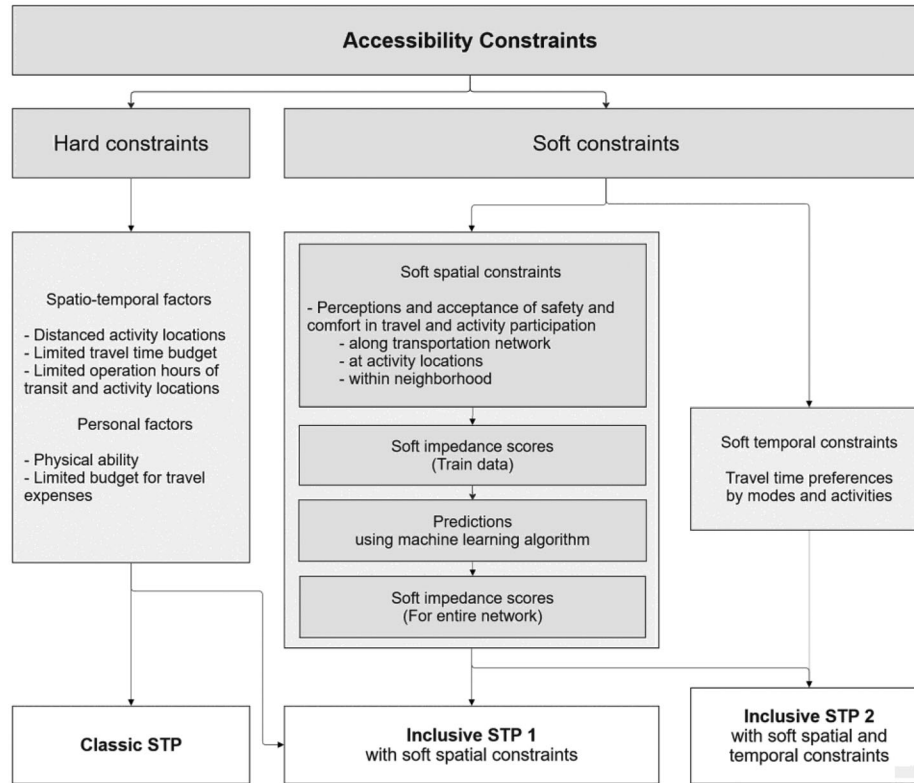


Figure 2. Framework for measuring person-based inclusive accessibility. *Note:* STP = space–time prism.

typically explicit, easily quantifiable, out of an individual’s control, and universally applied to everyone. Noncompliance with these constraints could restrict an individual from traveling. These constraints are predominantly spatiotemporal, such as distanced activity locations, limited travel time budget, and limited operation hours of transit and business activities. Personal limitations such as physical disability, limited income, and a fixed budget for travel expenses can also be hard constraints as they sometimes limit people from traveling.

Soft constraints represent the perceptual and subjective factors that individuals negotiate to make a trip viable to them. Compared to hard constraints, soft constraints are implicit and more personally varied, such as travelers’ overall attitude, risk perceptions, and acceptance. Note that soft constraints might reflect travelers’ spatial and temporal perceptions. Soft spatial constraints include travelers’ perceptions and acceptance of safety and comfort for certain travel modes and activities given the surrounding environments (e.g., land use and transportation). The soft spatial constraints are

context-dependent and can be measured in any geographic units: along transportation networks, at activity locations, and within neighborhoods.

Classic STP considers travel time budget a hard constraint and estimates it as available time for flexible activities given a traveler’s scheduling of required activities. Available time might be longer than a person’s preferred time to travel by each travel mode and to any destination. Inclusive accessibility treats time as a hard constraint when estimated conventionally and a soft constraint when derived as time preference. Similarly, other hard and soft constraints might not be mutually exclusive and vary from person to person. For instance, personal constraint, such as mobility disabilities, is a soft constraint for a person who can still travel at a slower pace but only to certain areas with wheelchair access. Similarly, safety, both traffic and crime related, might not always be perceptual. People might strictly avoid some crime-prone areas; in this case, it can be a hard constraint.

Measuring accessibility requires extensive data on hard and soft constraints. Data on hard constraints (e.g., transportation infrastructure, mobility services,

and activity locations) are easily available from secondary data sources. Data on soft spatial constraints, however, are limited, require time-consuming primary data collection, and do not guarantee extensive data coverage, which is problematic for incorporating soft constraints into accessibility measures.

ML prediction algorithms can help overcome this limitation (Figure 2). First, we can aggregate multiple soft constraints into a composite soft impedance score. Next, we train an ML algorithm that uses the soft impedance score from primary data as output. The input of this ML model can be any potential determinants of soft impedance score (e.g., characteristics of land use and transportation infrastructure, built and natural environment, and personal attributes). Finally, we predict the soft impedance score of the entire study area using the trained model. The most appropriate choice to construct inclusive STP is to collect data on hard and soft constraints along transportation networks, given that three core elements of an STP construct are anchors, a transportation network, and a velocity to traverse along the network (Miller 2017). We can collect sample data and predict soft impedance using ML at any geographic unit (e.g., streets, activity locations, neighborhoods), though, and embed them within the transportation network through spatial operations.

Inclusive Space–Time Prism

Inclusive STP is conceptualized as a subset of the classic STP that (1) is physically realizable (hard constraints), and (2) meets a minimum threshold with respect to individual perceptions and acceptance of safety and comfort. We develop two types of inclusive STPs: The first considers soft spatial constraints only, and the other considers both soft spatial and temporal constraints.

The inclusive STP with soft spatial constraints identifies the geographic coverage that is physically and psychologically accessible to a person from the activity location, considering their soft spatial constraints and other hard constraints specified in the classic STP. Inclusive STP with soft spatial and temporal constraints further considers time preferences with other hard and soft constraints. Thus, each STP construct is a subset of the previous one as they account for more individual-level travel perceptions and are more representative of the day-to-day travel that one might undertake using multiple modes.

Data

Primary Data

We collected primary data on individuals' daily travel patterns and experiences through a mobility survey. We focus on Columbus, Ohio, neighborhoods with higher percentages of public and active transportation usage both by choice and necessity. We recruited participants via advertisements on social media sites such as Facebook and Nextdoor, neighborhood commission meetings, and local social events.

Our mobility survey includes three steps: baseline, smartphone-based pop-up survey, and end survey. The baseline and end survey have questions on day-to-day travel patterns, preferences toward traveling by specific modes (transit and walking), and demographics. In addition, we display example photos of Columbus roads (captured from Google Street View) to learn about travelers' perceptions of safety, comfort, and willingness to use multiple modes within those road environments. We chose the sample roads in the baseline and end survey that represent the diverse travel environment of Columbus and allow us to maximize the intrapersonal variability in soft spatial constraints. The pop-up survey involves using the ArcGIS Field maps mobile app to complete surveys and a travel log over a week. During this survey, travelers took photos of some road segments on their routes and filled out similar information on safety, comfort, and willingness to use specific modes.

We have 100 street photos rated by each traveler who completed all survey steps. We use the following statements to rate each street photo using a Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*).

1. I am willing to walk on this road.
2. I feel safe from crashes when walking on this road.
3. The surrounding environment is pleasant.

This article analyzes results from forty travelers with complete survey data sets of 100 data points and trip data to demonstrate and illustrate our method.

Secondary Data

We collected secondary data on the existing road infrastructure and the built environment. Table 1 provides the data descriptions and their respective sources.

Table 1. Data description of road, sidewalk, and built environment attributes collected from secondary sources

Variable	Data type	Description	Source
Network characteristics			
Number of lanes	Continuous	Number of lanes available on each street, varies from 1–4	Mid-Ohio Open Data (MORPC 2021)
Speed	Continuous	Speed limit, between 15 and 70 mph	
Functional class	Categorical	Used principal arterial, minor arterial, major collector, minor collector, and local roads and excluded interstates, freeways, and ramps from our analysis	StreetLight Data (2021)
Road width	Continuous	Road width estimates based on the number of lanes multiplied by the standard lane width for each functional class, specified by the Federal Highway Administration, U.S. Department of Transportation	
Average daily traffic volume	Continuous	The average daily traffic volume on each road segment during 2021	
Sidewalk characteristics			
Sidewalk availability	Binary	1 if a sidewalk is available on the left, right, or both sides; otherwise 0	Mid-Ohio Open Data (MORPC 2021)
Sidewalk width	Continuous	Width of the available sidewalks, values range from 3–8 feet.	
Buffer zone	Binary	1 if any of these buffer types (barrier, brick, other, planters, tree, lawn) are available; otherwise 0	U.S. Geological Survey (2021)
ADA compliance of sidewalks	Binary	1 if the sidewalk is ADA compliant, otherwise 0	
Surface type of sidewalks	Binary	1 if the sidewalk surface is concrete-made, otherwise 0	
Land-use characteristics			
Light and dense vegetation within a 10-m buffer from the street centerline	Continuous	NDVI measured using Landsat 8 data (30m resolution) on 30 September 2021 NDVI value 0.3–0.4 is considered light vegetation and >0.4 is dense vegetation	

Note: ADA = Americans with Disabilities Act; NDVI = normalized difference vegetation index.

Method

This study demonstrates inclusive accessibility using network-based soft constraints that evaluate an individual’s travel perceptions along Columbus streets and time preferences for walking and transit use. We only consider the forward cones of network-based STP that identify parts of transportation networks reachable from a specific origin considering a traveler’s hard and soft constraints. We present these classic and inclusive STP constructs as

two-dimensional PNA measures for effective interpretation. Figure 3 provides a schematic diagram of measuring classic and inclusive access used in this study.

Modeling Hard Constraints

This study considers three indicators to denote hard constraints: a fixed activity location, a fixed travel time budget, and public transit routes and schedules. We find travelers’ fixed activity locations

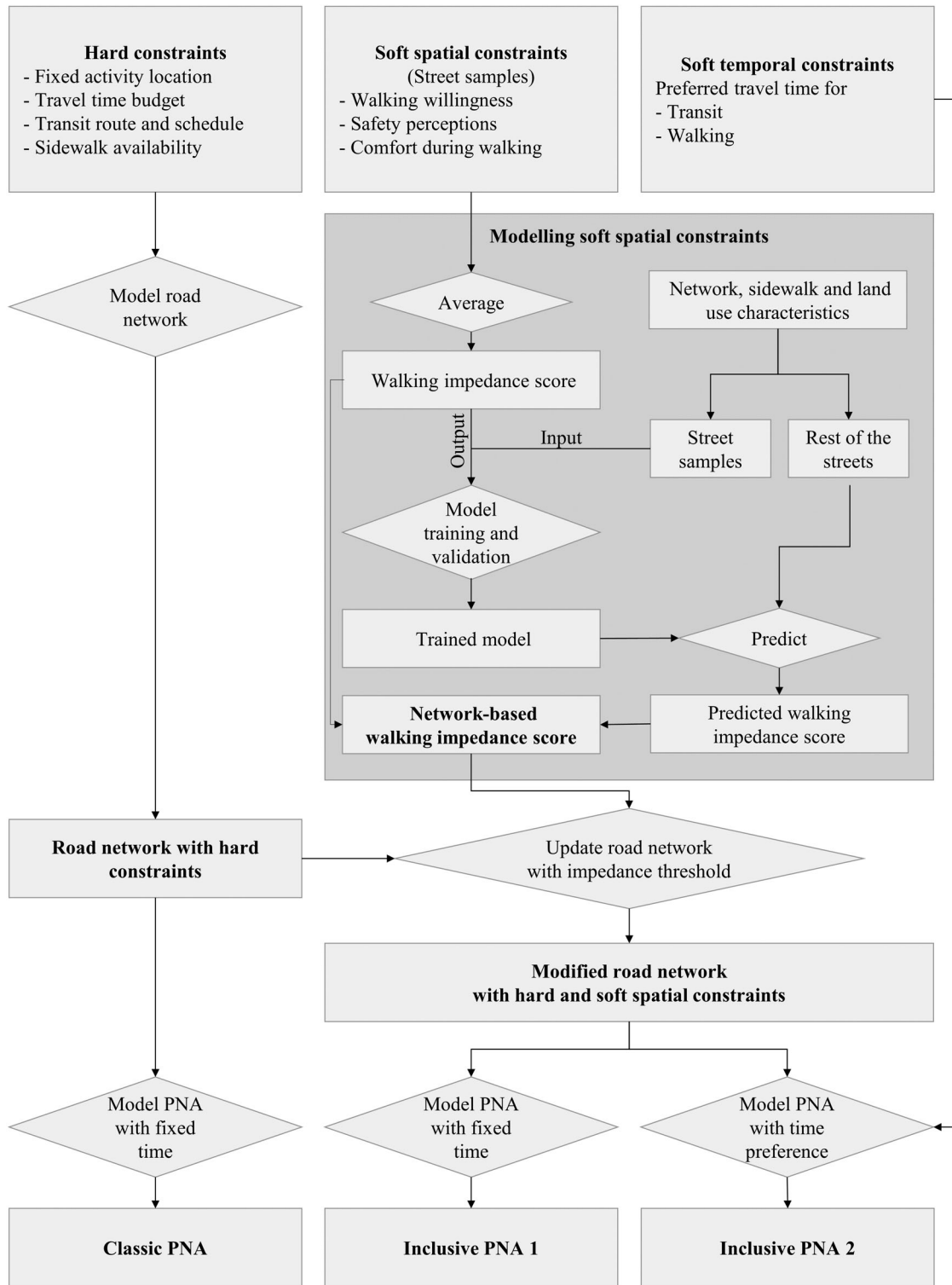


Figure 3. Schematic diagram of measuring classic and inclusive access used in this study. Note: PNA = potential network area.

from their trip data. For each traveler, we identify the origin and destination of each trip during the seven-day pop-up survey period. Then, we apply the density-based spatial clustering (DBSCAN)

algorithm to locate the most visited areas of the travelers (Sander et al. 1998; Campello, Moulavi, and Sander 2013). We use a minimum of five points in a cluster and a threshold distance of 400 m.

We assume that the top cluster with the highest number of points contains the traveler’s home location and use the centroid of that cluster as the fixed activity location of the respective traveler. We also collect transit route availability and schedules from static General Transit Feed Specification (GTFS) data of 6 December 2021 (GTFS 2020).

Modeling Soft Constraints

The middle block in Figure 3 explains the process of modeling soft spatial constraints. In this study, the ratings collected through the street surveys regarding willingness to walk, safety perception, and comfort in traveling within different road environments are considered soft spatial constraints. To simplify our method and calculation, we develop a walking impedance score as a composite indicator of the soft spatial constraints. The walking impedance score represents the mean of walking willingness, safety, and comfort within the surrounding environment for each traveler. The variables used to derive walking impedance scores do not require normalization, as they are all on the same 1-to-5 scale.

Because each traveler rates only a sample of Columbus streets ($n=100$), we use their individual survey responses as a training data set and apply ML algorithms to predict the walking impedance scores for the rest of the Columbus network. The output variable for the prediction models is the walking impedance score of each Columbus street, with values ranging from 1 to 5, where 1 represents the highest impedance, and 5 represents the least impedance. We use all variables listed in Table 1 as input data for predicting walking impedance scores.

We prepare training data sets for each individual by performing one-hot encoding for categorical variables and min-max scaling for continuous variables. Next, we perform cross-validation using repeated k -fold (sevenfold, three repeats) to evaluate model choices. We compare stochastic gradient descent, random forest (RF), multilayer perceptron, and support vector regressor (SVR) and use mean absolute error (MAE) in assessing model performances. Finally, we apply SVR with radial basis function (RBF) kernel and RF for modeling individual-level network-based impedance scores.

Based on our selected model, we use 80 percent of our data set for hyperparameter tuning and model training, the rest for validation, and finally, we

predict walking impedance scores for the entire street network of Columbus for each traveler. Using randomized search cross-validation, the model optimizes gamma, C, and epsilon parameters for the SVR models and the number of trees, maximum features, maximum depth, minimum samples split, minimum samples leaf, and bootstrap parameters for the RF models (Smola and Schölkopf 2004; Probst, Wright, and Boulesteix 2019). Once tuned, we estimate network-based walking impedance scores separately for each traveler.

In addition to the walking impedance score as a soft spatial constraint, we apply travelers’ preferred travel times for public transit use and walking as soft temporal constraints. These variables indicate travelers’ attitudes toward using specific modes regardless of the characteristics of the surrounding travel environment.

Classic PNA Based on Hard Constraints

The assumption for measuring classic PNA is that travelers start their trip at 8.00 a.m. on a regular weekday from an activity location, presumably their home location. We use the sidewalk availability and public transit route and schedule to model the road network with hard constraints. Then we apply a fixed travel time budget of sixty minutes to delineate the road networks that are physically accessible to this person from the activity location (leftmost column in Figure 3). We perform this analysis separately for each traveler in our study using an ArcGIS Network Analyst with Python script.

Inclusive PNA with Soft Spatial Constraints (IPNA 1)

The inclusive PNA follows the same procedure stated in the previous section, with additional consideration of walking impedance scores to represent the soft spatial constraints. We convert the classic measure to the inclusive accessibility approach by modifying the network and excluding the streets with a walking impedance score less than or equal to 3 (disagree to neutral). This modified network represents a walking-friendly travel environment based on the traveler’s perceptions. Using this modified road network, we identify parts of road networks that are not only physically accessible but also feel accessible

to this person from the fixed activity location using a fixed travel time budget of sixty minutes and public transit schedules (middle column in [Figure 3](#)).

Inclusive PNA with Soft Spatial and Temporal Constraints (IPNA 2)

In this step, we modify our inclusive PNA modeling criteria and use the travelers' transit and walking time preferences instead of a fixed travel time budget (the right-most column in [Figure 3](#)). This inclusive PNA model also uses the modified network that eliminates streets with higher walking impedances. The inclusive PNA developed in this step outlines the road network that is physically and psychologically accessible to this person and fulfills his or her mode-specific travel time preferences.

Estimating the Differences in Classic and Inclusive Accessibility

We estimate the differences in accessibility for each traveler based on the three PNA measures: a classic PNA with hard constraints, an inclusive PNA with soft spatial constraints (IPNA 1), and an inclusive PNA with soft spatial and temporal constraints (IPNA 2). First, we calculate the area accessible by each person using a 50-m buffer along their identified network of PNAs. Then, we calculate the percentage changes in accessible areas for both inclusive PNAs using the accessible area by the classic PNA as a reference. We also replicate this analysis using buffer distances of 75 m and 100 m to examine its sensitivity to buffer distances.

Case Studies

Soft Constraints Model Performance and Selection

[Table 2](#) summarizes the average MAEs estimated by performing cross-validations using four ML algorithms for each user. Overall, the average MAE

values of the user-specific cross-validated SVR and RF models are the lowest, indicating their better performances than the other two models.

Prediction of Network-Based Walking Impedance Scores as Soft Constraints

Considering similar model performances, we predict each user's walking impedance scores for the entire network using their individual SVR and RF models. In the individual-level RF models, the MAE values in the train data set range from 0.04 to 0.70 with a mean and standard deviation of 0.36 and 0.17, respectively, whereas the MAE values in the test data set range from 0.41 to 1.13 with a mean and standard deviation of 0.71 and 0.18, respectively. In the individual-level SVR models, the MAE values in the train data set range from 0.14 to 0.94 with a mean and standard deviation of 0.46 and 0.18, respectively, and the MAE values in the test data set range from 0.37 to 1.29 with a mean and standard deviation of 0.75 and 0.26, respectively. The tuned hyperparameters and MAE of each traveler's model are provided in [Appendix Table A.1](#) and [Table A.2](#).

[Figure 4A](#) illustrates the user-specific distribution of walking impedance scores predicted from SVR. The boxplots present the travelers' impedance score distributions in descending order of their mean and standard deviation estimated from the SVR predictions. [Figure A.1](#) in the [Appendix](#) provides the corresponding distributions estimated from RF models. Whereas the travelers' mean walking impedance scores are quite similar between SVR and RF, the interquartile ranges of the SVR model predictions are comparatively higher than the RF for most travelers. Especially for a few travelers, the RF model predictions are significantly concentrated around their mean, which is not the case for the SVR predictions of the same travelers. Also, the RF model predictions contain more outliers than SVR. These findings suggest that the

Table 2. Average mean absolute errors estimated from user-specific cross-validations for model performance evaluation

	Stochastic gradient descent	Support vector regressor	Random forest regressor	Multilayer perceptron regressor
Mean	0.73	0.71	0.71	0.74
Standard deviation	0.15	0.17	0.17	0.15
Maximum	1.12	1.19	1.08	1.13
Minimum	0.44	0.40	0.41	0.46

SVR models might be more consistent and capture a higher level of variance in the data set. Therefore, we choose the SVR model to predict impedance scores for the entire road network and develop inclusive accessibility.

We observe significant differences in walking impedance scores among travelers indicating their varying levels of sensitivity to street characteristics. As we move from the left to the right side of the graph (Figure 4A), travelers become more sensitive to infrastructure and land-use conditions as their mean walking impedance score decreases. Nine travelers from the left are least sensitive, as their mean walking impedance scores are above 4 with comparatively smaller interquartile ranges, reflecting their preference to walk on most Columbus streets. Meanwhile, the mean walking impedance scores are below 3 for the six travelers from the right, indicating their reluctance toward walking. These travelers are perhaps highly sensitive and anticipate higher mobility constraints or unpleasant travel experiences in most parts of Columbus. The mean walking impedance scores of the rest of the travelers fall within—between 3 and 4. These travelers show wide variations in their perceived

barriers during walking trips representing their moderate levels of sensitivity toward different travel environments.

Figure 4B illustrates the current walking pattern of these travelers for work, nonwork, and recreational trips, following the same order of travelers illustrated in Figure 4A. For each traveler, a dot in Figure 4B indicates that he or she frequently takes walking trips for daily work commutes (e.g., full- or part-time jobs and schools), or weekly nonwork essential trips (e.g., groceries and health care) and recreational trips (e.g., park, green space, and other entertainment destinations). Apparently, the least sensitive travelers do not walk much except for recreational trips. The highly sensitive travelers mostly walk for nonwork and recreational purposes. Meanwhile, the moderately sensitive travelers who exhibit varied walking preferences based on street characteristics are the experienced pedestrians. They frequently walk for both commuting and noncommuting trips. These travelers' current transit and car usage are shown in Figure A.2 in the Appendix. Most travelers use private vehicles regardless of their trip purpose. Several ride public transit for work trips and very few for nonwork purposes.

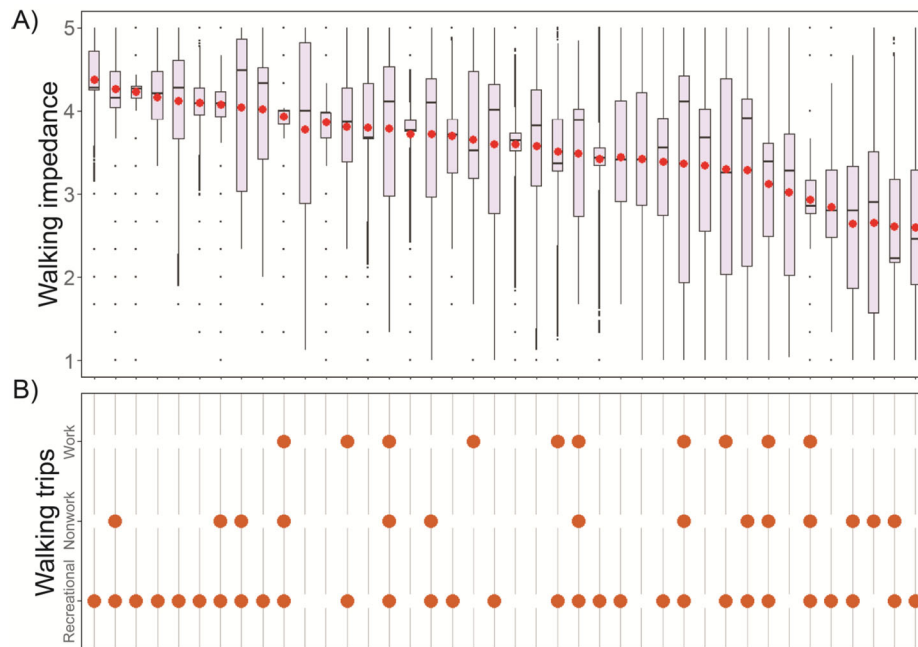


Figure 4. (A) Distribution of walking impedance scores for each user, including both survey responses and predicted scores from support vector regressor. The red dot in each boxplot represents the mean value. (B) Current walking patterns of travelers for different trip purposes. Each column in both plots corresponds to the same traveler.

Inclusive Accessibility

Figures 5 through 7 illustrate the differences in walking impedance scores and PNA measures for three representative travelers who are women with different socioeconomic backgrounds. Both Travelers 1 and 2 are White women in their late twenties, where the first person has a full-time job with a moderate income, and the second person has a part-time job with a low income. Traveler 3 is a middle-aged Black woman with a high income and a full-time job. The walking perceptions of these travelers are, respectively, least, moderate, and highly sensitive to street characteristics. The red-to-green color scheme on the left-side figures indicates the Likert scale (disagree to agree) of walking impedance scores of Columbus streets. In Figure 5A, most streets appear in green colors, as this White woman with moderate income perceives no barriers to walking except for a few major arterial roads with higher speeds. In contrast, most streets in Figure 7A are red colored as this middle-aged Black woman finds most streets problematic for walking except those near their fixed activity location. The walking impedance scores from the low-income White woman in Figure 6A, however, display significant variations in their walking preferences. In all cases, the neighborhood streets near their fixed activity locations, presumably their home location, are scored as 5, indicating that they feel comfortable walking around their known neighborhoods.

The figures on the right represent their accessibility using classic and inclusive PNA measures. Streets marked in blue, yellow, and red, respectively, outline the classic PNA with hard constraints, inclusive PNA with soft spatial constraints, and inclusive PNA with soft spatial and temporal constraints. For all cases, the area reachable by the traveler shrinks as we approach more conservative measures and include perceptions and time preferences. The deviation between classic PNA and inclusive PNA with walking constraints, however, is minimal for the moderate-income White woman in Figure 5B. In contrast, it makes a significant difference when we also include their travel time preferences for transit and walking. Conversely, we can observe substantial differences in accessible areas delineated by all three PNA measures for travelers in Figures 6B and 7B.

Changes in Accessibility Based on the Considerations of Soft Constraints

Figure 8 shows the areal differences between classic and inclusive PNAs using a 50-m buffer along the network, following the same order of travelers as in Figure 4. As indicated, the area accessible by inclusive PNAs is smaller compared to the classic PNA for all travelers. When we only consider the soft spatial constraints, however, the percentage

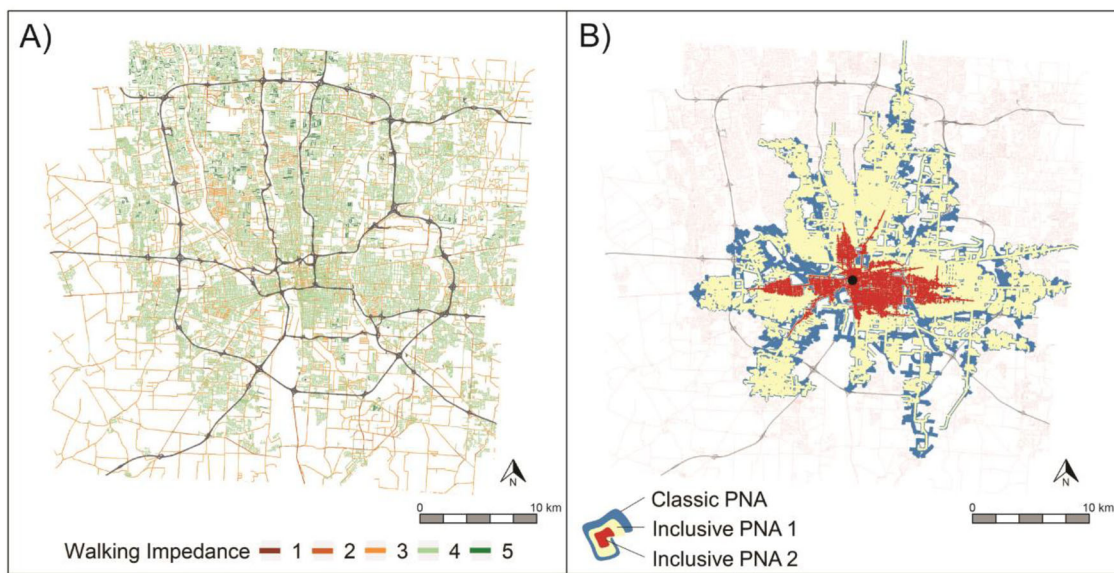


Figure 5. (A) Predicted walking impedance scores and (B) classic and inclusive potential network area (PNA) for a representative traveler (White woman in late twenties with moderate income and working full time) who is less sensitive to the travel environment.

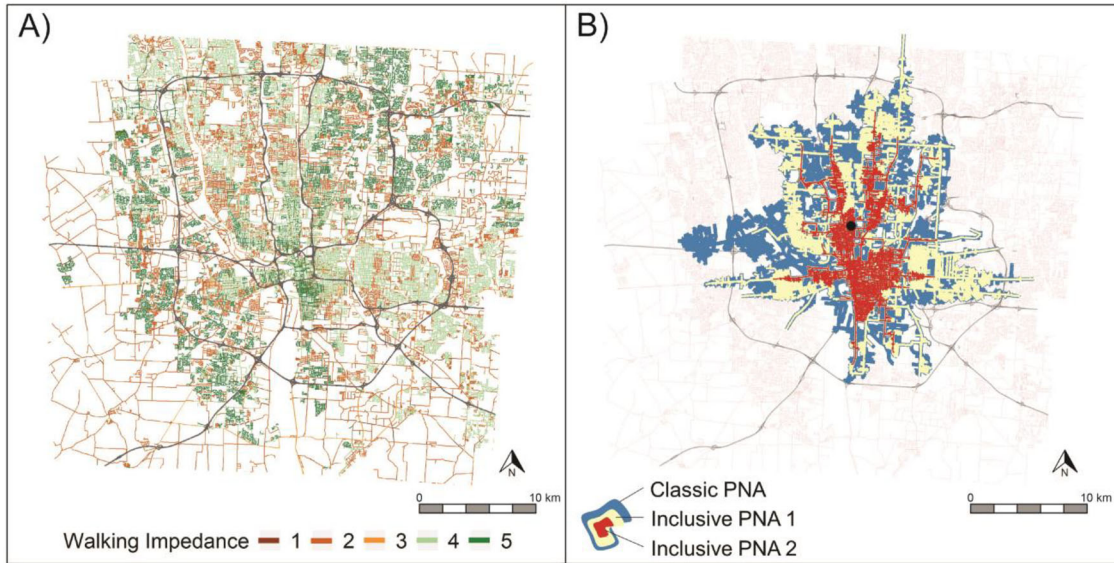


Figure 6. (A) Predicted walking impedance scores and (B) classic and inclusive potential network area (PNA) for a representative traveler (White woman in late twenties with low income and working part time) who is moderately sensitive to the travel environment.

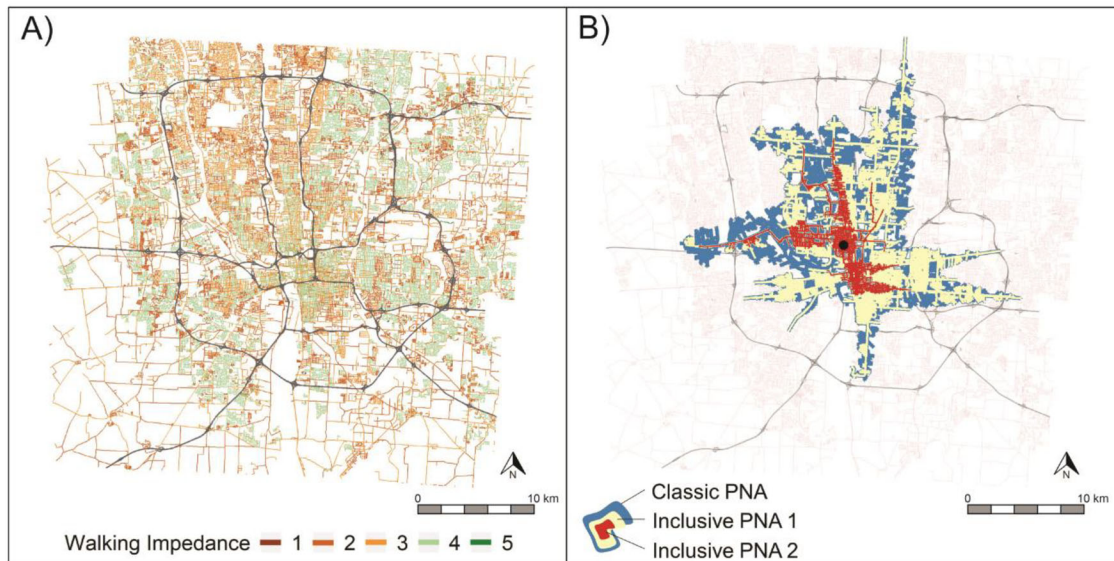


Figure 7. (A) Predicted walking impedance scores and (B) classic and inclusive potential network area (PNA) for a representative traveler (middle-aged Black woman with high income and working full time) who is highly sensitive to the travel environment.

decline in IPNA 1 increases with the increase in travelers' sensitivity to land use and street conditions (Figure 8A).

On the other hand, the percentage decline in IPNA 2 is substantial for most travelers, regardless of their sensitivity levels (Figure 8B). In such cases, though, the decline in access negatively correlates with the preferred travel time for transit use and

walking (Figure 9). In other words, regardless of the perceptions of the built environment and safety, the accessible area of travelers decline with their low interest in public transit use and walking. We find similar results from the analysis using 75-m and 100-m buffers, indicating the robustness of this analysis regardless of the buffer distances (Figures A.3 and A.4 in the Appendix).

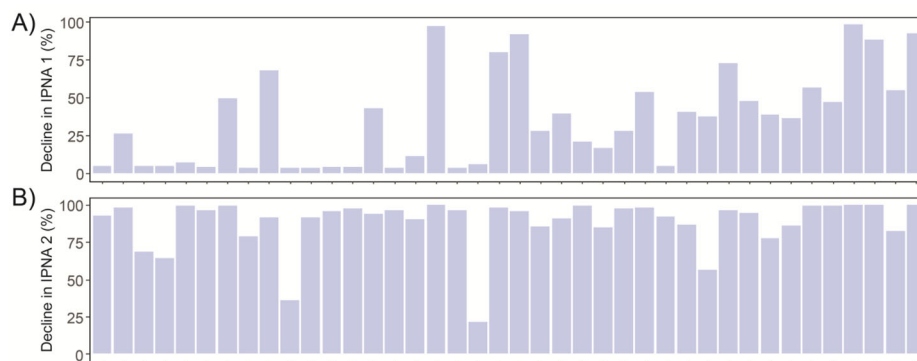


Figure 8. Percentage decline in area accessible by (A) IPNA 1 and (B) IPNA 2, compared to the classic potential network area (PNA). The accessible area is calculated using a 50-m buffer along the PNA networks.

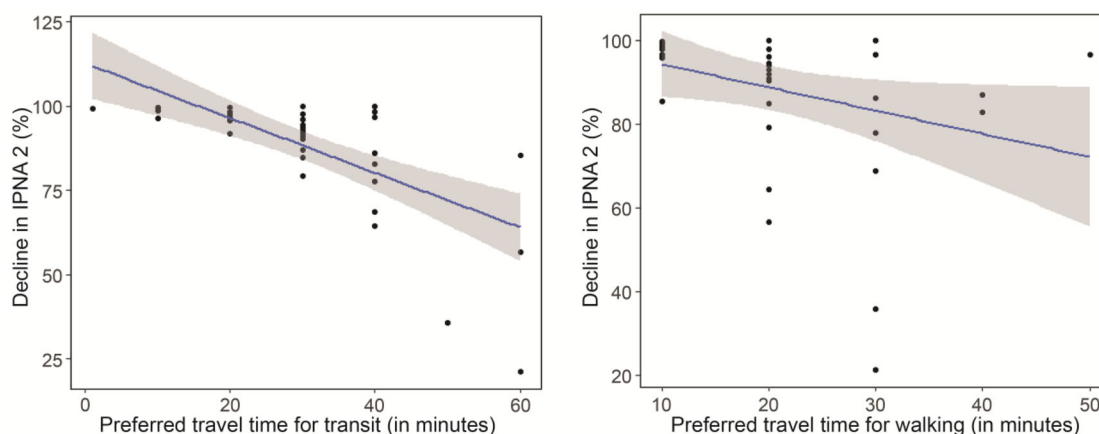


Figure 9. Correlation between mode-specific travel time preferences and the percentage decline in access using inclusive potential network area (PNA) with soft spatial and temporal constraints.

Discussion

Summary of Results

This study conceptualizes an inclusive accessibility measure that integrates physical and perceptual travel barriers as hard and soft constraints. We present a method to measure inclusive accessibility with a mobility survey data set of forty travelers in Columbus, Ohio.

Addressing the heterogeneity in travel perceptions into accessibility measures is a unique contribution of this study. Despite its significance, personal travel perceptions are challenging to capture due to their diverse and distinctive nature. This study overcomes that problem by applying ML algorithms in quantifying individual-level mobility perceptions along the network. This method has the potential for predicting perceptions as impedance or friction parameters in other modeling approaches, such as gravity-based accessibility measures and spatial interaction models.

The study finds that travelers' perceptions of mobility barriers and accessibility are sensitive to different travel environments where the level of sensitivity varies by their current travel patterns and exposure. On the one hand, travelers who do not walk much at present feel indifferent to street conditions. These travelers perceive Columbus as walkable, perhaps a reflection of their limited exposure to the current walking environment and unawareness of mobility barriers within Columbus. On the other hand, travelers with high sensitivity to street characteristics find Columbus less walkable. These travelers are mainly interested pedestrians but are extremely concerned about the surrounding environments and safety. Their preferred standards for a walking environment are quite high as they occasionally walk, mainly for noncommuting and recreational purposes. The rest of the travelers are mainly frequent pedestrians with a keen interest in active travel with moderate levels of sensitivity to street

conditions, consistent with findings from past research (Sener, Eluru, and Bhat 2009; Delbosc and Currie 2012). They are perhaps aware of the existing sidewalk and pedestrian safety conditions around Columbus, and find it less problematic, especially on frequently visited routes.

Considering travel perceptions and time preferences makes inclusive access more realistic and sensitive to people's actual travel by eliminating the overestimations of classic measures. For all travelers in this study, this measure is notably smaller than their classic accessibility, indicating overestimation in the latter measure. This finding also resonates with the past accessibility measures using objective (transport infrastructure and built environment) and subjective indicators (mobility perceptions and willingness; Gebel et al. 2011; Lättman, Olsson, and Friman 2016, 2018; Ma and Cao 2019; J. Ryan and Pereira 2021). Additionally, this study reveals that the magnitude of the decline from classic to inclusive access varies by travelers' sensitivity to travel environments. This variation dissipates, however, when we consider mode-specific time preferences, and the corresponding inclusive PNA becomes significantly smaller than the classic PNA. This points out overestimations in the fixed travel time budget of sixty minutes assumed in past studies (Ahmed and Stopher 2014; Lee and Miller 2018, 2019; Qin and Liao 2021), which we also use to delineate our classic and first inclusive PNA measures. The actual length of transit rides and walking trips that people might prefer to undertake is much shorter than sixty minutes, resulting in substantial differences in classic and the second inclusive PNA measures.

Large-scale application of inclusive access could identify *who* experiences limited access to *where* and its socioeconomic differences. For instance, the inclusive accessibility measures for three women illustrate that Black and low-income women are more sensitive to the travel environment and experience higher obstacles than the moderate-income White woman. This finding underscores accessibility inequity for travelers with financial limitations and racially diverse backgrounds. Classic access cannot address such differences due to the assumption of homogenous physical and financial abilities, as well as equal acceptance of risks, standards for comfort, and other constraints. Urban design and infrastructure planning in the United States are historically discriminating, however, leading to substantial

differences in ability and perceptions across individuals. Economically and racially disparate communities tend to have lower expectations for comfort as they are already served with poor-quality infrastructure and services and have limited financial ability to spend on travel. Moreover, marginalized populations, as well as women, children, and the elderly, are at a higher risk of physical injuries, assaults, and harassment, making them less acceptant to risks. Our measure accounting for such income, racial, and gendered differences in abilities and perceptions makes it more inclusive to vulnerable communities who are traditionally overlooked by existing accessibility measures.

Limitations and Future Directions

This study has several limitations related to the intensity and representativeness of the data. First, our prediction of walking impedances and accessibility might be more representative of planned travel, such as daily work travel and periodical nonwork travel to essential activities. Second, although we strive to maintain the reliability of survey responses, we cannot verify some of these responses, such as if any travelers' skewed walking impedance pattern is not an outcome of their inattentive responses. Third, the accuracy of network-level soft constraint measures depends on the sample data size available from each traveler. This study uses a relatively small data set collected from each participant due to time and resource limitations, although a larger data set might have produced better model performances. Finally, the transferability of the person-based models in predicting inclusive access for another traveler of similar characteristics is yet unknown. Specifically, the soft constraints models in this study can predict the mobility perceptions of one individual traveler without providing further guidance on translating these models and findings for another individual outside the sample participants.

Our current application focuses on acceptance and perceptions of safety and comfort along transportation infrastructure because this is a major factor influencing social and gender differences in active travel. This concept and theoretical framework are applicable in other study contexts, however. Future studies could consider other personal hard constraints, as well as activity-related and area-specific

soft constraints using the same data collection and modeling mechanism. Future extensions could also update the method of including soft constraints into STP measures and shift from the current deterministic approach to a probabilistic measure with soft constraints integrated as fuzzy logic.

The inclusive accessibility concept recognizes hard and soft constraints as limitations associated with space and time. People also experience certain hard and soft social constraints in travel and activity participation, however. For instance, some social norms and conventions are hard constraints enforcing limited physical access to certain places and activity participation (e.g., age restrictions for visiting bars and social status for accessing certain elite clubs). Again, perceptions of social space (e.g., neighborhood familiarity, sense of belongingness and acceptance, and conformity to other lifestyle choices) are soft constraints that indirectly impede people from traveling to particular destinations. Future studies could consider these social constraints in designing inclusive access.

This research discusses an approach to integrating soft constraints into person-based STP measures. Although effective in exploring the heterogeneities in mobility perceptions, the person-based STP measure has limited capability to generalize the findings to larger populations. As a solution, future research might develop an approach to aggregating person-based inclusive accessibility into a place-based measure that evaluates hard and soft constraints using data from a larger sample of travelers and accounting for their socioeconomic statuses. Building on our findings of accessibility inequity experienced by low-income and racially diverse travelers, future studies with a larger sample size could help quantify the intensity of perceived mobility barriers and limited access among socioeconomically vulnerable communities. Moreover, future research could use the soft constraints and their variations across social groups in demonstrating need-specific transportation network designs with special emphasis on mobility-disadvantaged communities.

Conclusion

This study presents the theoretical background of a novel inclusive accessibility concept and an example method for operationalizing the concept. We develop the person-based inclusive STP that

converges space–time limitations as hard constraints and travel perceptions along transportation networks as soft constraints. The results highlight significant variations in the perceived mobility barriers and corresponding inclusive accessibility measures across individuals depending on their current mobility pattern and exposure. The shift from classic to inclusive access lowers potential mobility, identifies a person's physically and psychologically accessible geographic space, and makes the measure more sensitive to actual travel.

The inclusive accessibility approach might help us locate the inequalities around the urban transportation system from a mobility justice perspective. Researchers and professionals can use this method to understand the spatial differences in perceived mobility barriers and accessibility across socioeconomically diverse communities. Inclusive accessibility could also serve as a performance indicator in evaluating potential transportation investments and identifying their beneficiaries. Thus, inclusive accessibility can facilitate the decision-making process while designing root-level, community-specific transportation plans that aim to replicate personalized and community-specific mobility needs and eliminate their perceived barriers.

Disclosure Statement

No potential conflict of interest was reported by the authors.

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Appendix

Table A.1. The tuned hyperparameters and mean absolute errors (MAEs) in the train and test set of support vector regressor models

Traveler	Gamma	C	Epsilon	MAE in train set	MAE in test set
1	0.01	10	0.01	0.548219	0.612474
2	0.001	100	0.01	0.353165	0.405908
3	0.5	1	0.1	0.394138	0.474494
4	1.00E-04	0.1	0.001	0.743163	0.722403
5	0.2	1	0.001	0.453197	0.692305
6	0.001	100	0.001	0.288296	0.375987
7	0.5	1	0.1	0.520531	0.963988
8	0.2	1	0.1	0.371523	0.674623
9	0.1	100	0.001	0.145183	0.866691
10	0.001	100	0.01	0.665485	0.528593
11	0.1	10	0.1	0.514909	1.097387
12	0.01	100	0.001	0.476775	0.759367
13	0.001	10	0.001	0.377839	0.413945
14	0.5	0.1	0.1	0.568513	0.475638
15	0.5	1	0.001	0.338338	0.724361
16	0.001	100	0.001	0.696467	1.178460
17	0.5	10	0.01	0.223709	1.056023
18	0.1	1	0.1	0.943697	1.303788
19	0.5	0.1	0.01	0.775269	0.926742
20	0.001	100	0.001	0.622853	0.663985
21	0.01	10	0.1	0.361629	0.389462
22	0.1	10	0.1	0.405359	1.314321
23	0.1	10	0.01	0.337907	0.733076
24	0.001	10	0.01	0.642426	0.709012
25	1.00E-04	100	0.001	0.66628	0.546868
26	0.5	10	0.1	0.17942	0.815692
27	0.1	10	0.1	0.417582	0.658755
28	0.5	1	0.1	0.377138	0.524538
29	0.001	100	0.01	0.432898	0.643338
30	0.2	10	0.001	0.308959	0.905198
31	0.5	1	0.1	0.385538	0.793541
32	0.1	10	0.01	0.261958	0.827417
33	0.01	100	0.01	0.435514	0.825864
34	0.1	10	0.001	0.260893	0.480277
35	0.1	10	0.1	0.457476	1.295155
36	0.01	100	0.01	0.538089	0.845017
37	0.001	100	0.1	0.853048	1.024896
38	0.01	1	0.01	0.710174	1.040916
39	0.01	100	0.1	0.340032	0.573382
40	0.2	1	0.001	0.361875	0.509135

Table A.2. The tuned hyperparameters and mean absolute errors (MAEs) in the train and test set of random forest models.

Traveler	N estimators	Minimum samples split	Minimum samples leaf	Maximum features	Maximum depth	Bootstrap	MAE in train set	MAE in test set
1	400	5	4	sqrt	100	True	0.560306	0.493528
2	1,200	10	1	auto	110	True	0.240836	0.658693
3	2,000	10	4	sqrt	20	True	0.561526	0.561008
4	1,200	10	4	sqrt	50	True	0.632867	0.879767
5	1,200	10	1	auto	110	True	0.360545	0.752029
6	1,400	10	2	auto	40	False	0.200783	0.516286
7	400	5	4	sqrt	100	True	0.697499	0.817775
8	1,800	5	1	auto	70	True	0.285957	0.568124
9	1,000	5	2	auto	10	True	0.331854	0.639198
10	1,000	5	2	auto	10	True	0.331658	0.824994
11	1,600	2	1	auto	110	True	0.327906	1.135370
12	1,600	2	4	auto	60	False	0.473298	0.593175
13	1,200	10	4	sqrt	50	True	0.298236	0.470138
14	1,800	10	1	sqrt	110	False	0.323767	0.475883
15	200	5	1	sqrt	90	False	0.216421	0.564069
16	200	5	1	sqrt	90	False	0.272767	0.998911
17	400	5	4	sqrt	100	True	0.672073	0.936612
18	1,000	10	4	auto	80	False	0.552993	1.132590
19	1,000	10	2	auto	40	False	0.513075	0.773707
20	1,600	10	2	sqrt	90	True	0.590816	0.723479
21	600	5	2	auto	20	True	0.227694	0.448239
22	1,600	10	2	sqrt	90	True	0.706948	0.646815
23	400	2	1	sqrt	70	False	0.036505	0.749458
24	200	5	1	sqrt	90	False	0.199720	0.609531
25	400	5	4	sqrt	100	True	0.590769	0.680762
26	1,600	2	1	auto	110	True	0.222439	0.767510
27	1,600	2	1	auto	110	True	0.218768	0.686326
28	400	2	1	sqrt	70	False	0.002094	0.620917
29	400	10	1	auto	100	True	0.33394	0.782547
30	1,200	2	2	sqrt	30	False	0.37333	0.922417
31	1,000	5	2	auto	10	True	0.347448	0.717737
32	400	10	1	auto	100	True	0.375028	0.665327
33	1,200	10	1	sqrt	40	False	0.362406	0.807358
34	2,000	2	1	sqrt	70	True	0.206354	0.483224
35	400	2	1	sqrt	110	True	0.354000	0.872120
36	400	10	1	auto	100	True	0.468183	0.696857
37	400	2	1	sqrt	70	False	0.000473	1.127262
38	1,800	5	4	sqrt	70	False	0.558743	0.865433
39	600	10	2	sqrt	30	False	0.294457	0.631404
40	800	2	4	auto	30	True	0.381014	0.418687

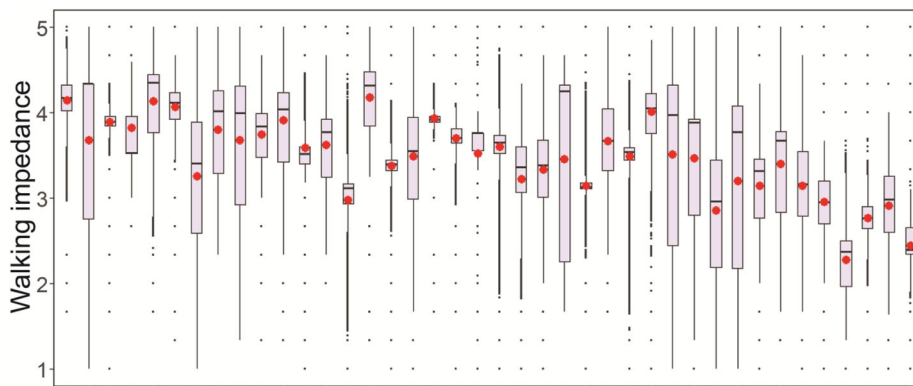


Figure A.1. Distribution of walking impedance scores for each user, including both survey responses and predicted scores from random forest models. The order of travelers follows the same order presented in [Figure 4](#).

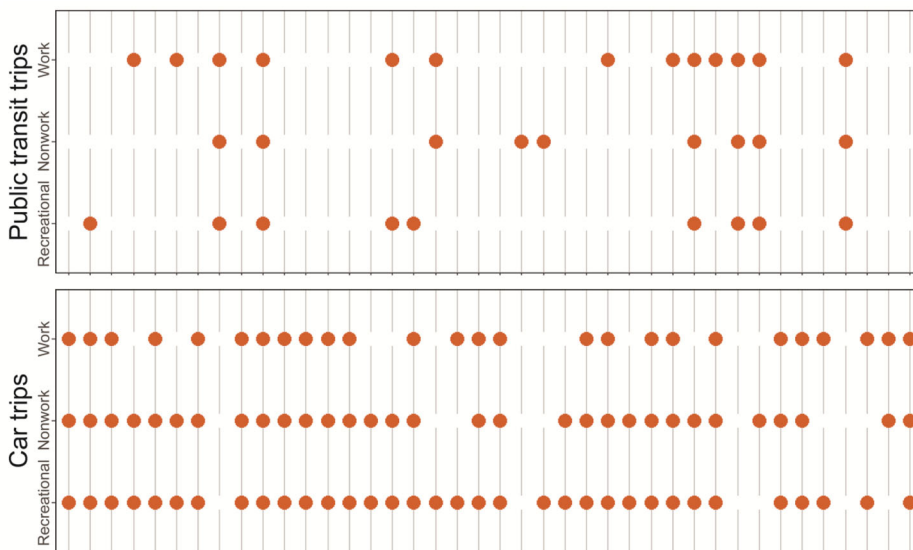


Figure A.2. Transit and car use patterns of travelers for different trip purposes.

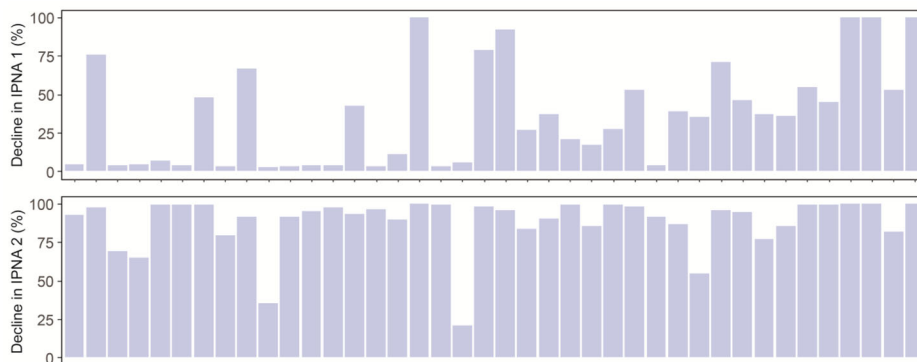


Figure A.3. Percentage decline in area accessible by IPNA 1 and IPNA 2, compared to the classic potential network area (PNA). The accessible area is calculated using a 75-m buffer along the PNAs.

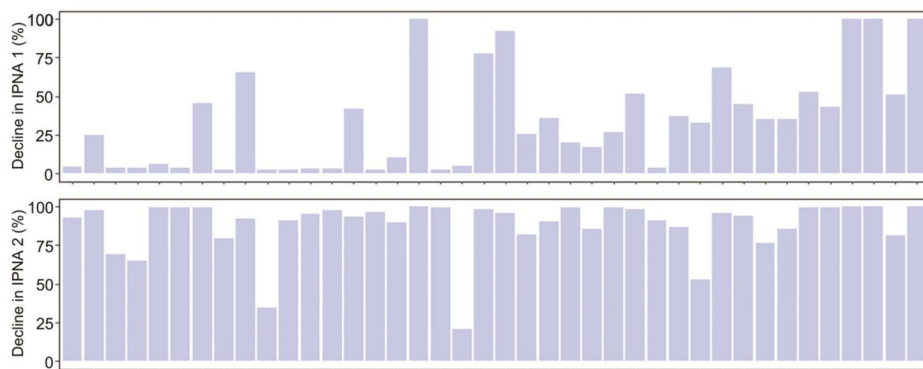


Figure A.4. Percentage decline in area accessible by IPNA 1 and IPNA 2, compared to the classic potential network area (PNA). The accessible area is calculated using a 100-m buffer along the PNAs.