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Inclusive accessibility: Analyzing socio-economic disparities in perceived accessibility

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ABSTRACT

Existing accessibility measures mainly focus on the physical limitations of travel and ignore travelers' perceptions, behavior, and socio-economic differences. By integrating approaches in time geography and travel behavior, this study introduces a bottom-up inclusive accessibility concept that aggregates individual-level travel perceptions across socio-economic groups to evaluate their multimodal access to opportunities. We classify accessibility constraints into hard constraints (physical space-time limitations to travel) and soft constraints (perceptual factors influencing travel, such as safety perceptions, comfort, and willingness to travel). We categorize travelers into 12 mutually exclusive socio-economic groups from a mobility survey dataset of 477 travelers. We apply a support vector regressor-based ensemble algorithm to estimate network-level walking perception scores as soft constraints for each social group. We derive group-specific inclusive accessibility measures that consider space-time limitations from transit and sidewalk networks as hard constraints and minimize the group-specific soft constraint to a certain threshold. Finally, we demonstrate the effectiveness of group-specific inclusive accessibility by comparing it with the classic access measure. Our study provides scientific evidence on how people of varying socio-economic statuses perceive the same travel environment differently. We find that socio-economically disadvantaged communities experience higher mobility barriers and lower accessibility while walking and using transit in Columbus, OH. Our study demonstrates a transition from person- to place-based accessibility measures by sequentially quantifying mobility perceptions for individual travelers and aggregating them by social groups for a large geographic scale, making this approach suitable for equity-oriented need-specific transportation planning.

1. Introduction

Urban planners frequently rely on accessibility metrics, an evaluation of people's potential mobility, to assess and improve transportation system performance (Boisjoly & El-Geneidy, 2017). Typically, these metrics are estimated in a generalized form for populations residing within an identifiable geographic area, such as a neighborhood or city, considering their mode-specific access to essential opportunity locations (e.g., job, food, healthcare, and education) (El-Geneidy & Levinson, 2022). These place-based measures, however, often overgeneralize accessibility, assuming it is socially invariant within a given space (Miller, 2007). This can lead to inaccurate and flawed transportation project evaluations and decision-making, particularly from the equity perspective. An alternative approach, person-based accessibility measures, estimates potential mobility at an individual level (Miller, 2007). Despite its ability to better capture the spatio-temporal complexities of travel, the disintegrated nature of the person-based measure, along with limited guidance for generalizing it to a larger scale, hinders its usability in urban planning practices (Geurs & Van Wee, 2004).

Additionally, classic accessibility measures mainly consider the physical, space-time constraints (e.g., land use-transportation environment, and time) and overlook the behavioral, perceptual, and social aspects of travel (El-Geneidy & Levinson, 2006; Geurs & Van Wee, 2004). People of different ages, gender, income, and race perceive physical environments and time differently due to their unique past travel experiences, attitudes, and lifestyle choices (Alfonzo, 2005; Hsu &

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Lee, 2017; Iseki & Smart, 2012; Ma & Cao, 2019; Singleton & Clifton, 2014). These diverse travel perceptions reflect how people feel about traveling across certain networks and places and make their day-to-day travel decisions (Aziz et al., 2018; Delbosc & Currie, 2012; Ma & Cao, 2019; Spears, Houston, & Boarnet, 2013). Travel perceptions serve as a bridge between the locations and activities people can reach, their potential mobility, and the ones they choose to travel in reality, their actual mobility. Classic accessibility measures, due to being an estimation of the former while neglecting the latter, often overestimate the perceived ability and willingness of travelers to reach places, especially those from socio-economically disadvantaged communities (Ryan & Pereira, 2021; Van der Vlugt, Curl, & Wittowsky, 2019).

Data collection is a key challenge in the existing perceived accessibility research incorporating travel behavior and perceptions. While measuring access, these studies evaluate people's perceptions (e.g., travel willingness, ease, convenience, and satisfaction) toward transportation infrastructure, mode, travel time, and activities (Cheng & Chen, 2015; Hawthorne & Kwan, 2012; Hess, 2009; Lattman, Olsson, & Friman, 2018; Ryan & Pereira, 2021; Ryan & Robinson, 2016; Van der Vlugt et al., 2019; Van der Vlugt, Curl, & Scheiner, 2022). These perceptions vary widely among different genders, ages, and social groups, underscoring the need to integrate travel perceptions to mitigate overestimations in existing measures, as well as to capture the social, gender, and age differences in accessibility (Jamei, Chan, Chau, Gaisie, & Lattman, 2022). However, these studies, relying solely on primary data and statistical approaches (Jamei et al., 2022), are unable to comprehensively capture the spatiotemporal heterogeneities in travel perceptions considering individuals' socio-economic backgrounds as well as the physical characteristics of the land use-transportation environments. One way to overcome this data limitation is to augment the perception data through additional machine learning (ML) predictive modeling to depict an overall picture of travel perceptions and their spatial variabilities across road environments, modes, and socioeconomic communities.

This study introduces a novel, bottom-up inclusive accessibility concept that first integrates travel perceptions into multimodal accessibility estimated for an individual and then demonstrates a method for aggregating the measure across socio-economically diverse communities. This measure categorizes accessibility constraints into two parts: hard constraints (i.e., objective, non-negotiable, physical barriers to travel) and soft constraints (i.e., subjective, negotiable, perceptual aspects of travel). We conceptualize inclusive accessibility as a subset of classic accessibility that is physically accessible and accounts for some psychological barriers (e.g., perceptions and acceptance of safety and comfort) that individuals and communities experience in their day-to-day travel.

This study develops a hierarchical modeling approach to measuring inclusive accessibility across diverse social groups. The objectives of this paper are to (1) design a group-based inclusive access measure that incorporates hard and soft constraints of social groups, and (2) demonstrate the variations in classic and inclusive access measures across social groups. We conducted a mobility survey in Columbus, OH, USA, to gather detailed individual-level travel perception data to represent soft constraints. Since the mobility survey dataset only contains soft constraint measures for certain streets of Columbus, we develop a support vector regressor (SVR)-based ensemble model that predicts network-specific soft constraints for 12 mutually exclusive social groups, categorized based on their income, race, and gender, and then apply these estimates in measuring classic and inclusive access.

This study has several contributions. First, inclusive accessibility is an advancement of existing space-time measures due to its consideration of perceptual factors of travel in measuring multimodal accessibility across individuals and social groups. This incorporation of travel perceptions makes accessibility measures more realistic and more likely to resemble peoples' actual travel behavior. Second, the group-based approach enables a transition of inclusive access from person- to place-based measures. Instead of measuring access for a particular individual or the overall population, we measure spatial variations in travel perceptions and inclusive access for social groups. This approach allows us to overcome the limitations of both person- and place-based measures and will help create policies that maximize accessibility to each social group. Lastly, the group-based inclusive measure, due to its capability to capture the spatial-social differences in travel needs and accessibility, is more applicable in designing need-specific transportation interventions.

2. Conceptual foundations

The inclusive access concept advances classic access measures by integrating both hard and soft constraints of travel. Sections 2.1, 2.2, and 2.3, respectively, discuss: the theoretical foundations of classic accessibility concepts, perceived accessibility as an extension of classic measures, and inclusive accessibility as an advancement of previously established perceived accessibility measures. Section 2.4 elaborates another crucial contribution of this paper – utilizing ML-based ensemble modeling in quantifying group-specific soft constraints.

2.1. Classic accessibility

Classic accessibility measures evaluate people's ability to reach essential services and opportunity locations by traditionally focusing on the physical characteristics of the land use-transportation environment and time limitations of travel and activity participation (Levinson & Wu, 2020). Classic accessibility measures predominantly consider three objective criteria of travel: 1. Spatial distribution of service and opportunity locations, 2. Availability of transportation networks and modes, and 3. Personal, activity- or mode-related time limitations (El-Geneidy & Levinson, 2006). Based on these basic components, the accessibility measure evaluates the physical ability of individuals and communities to reach opportunity locations using a travel mode within a time budget (El-Geneidy & Levinson, 2006).

Accessibility measures can be categorized into two types based on the scale of analysis, namely place-based and person-based (Levinson & Wu, 2020; Miller, 2007). Place-based measures are proximity-based measures that evaluate potential mobility and activity participation for people residing in a geographic area (e.g., neighborhood and city). Such measures support evaluating mode-specific accessibility for any geographic boundaries, making it a popular evaluation metric in transportation planning (El-Geneidy & Levinson, 2022; Geurs & Van Wee, 2004). However, place-based approaches assume equal accessibility for all residents within the same geographic space and cannot capture the spatiotemporal complexities and idiosyncrasies of travel across people and communities (Miller, 2007).

In contrast, person-based measures follow time geographic theory and define an individual's potential mobility based on their time allocation across space (Hagerstrand, 1970; Miller, 2017). Person-based measures effectively capture the underlying heterogeneities in travel and activities across individuals. Yet, these measures are invariant to spatial scales and geographic boundaries with limited scope for generalization for a larger population and application in large-scale planning practices (Kwan & Weber, 2008; Miller, 2007). A research gap exists in designing a method to transition between scales that avoids the overgeneralization of place-based measures while also being transferable to a larger scale from person-based measures.

2.2. Perceived accessibility

Perceived accessibility measures, extending classic ones, consider both subjective and objective constraints to better understand social, demographic, and travel-related differences in accessibility (Cheng & Chen, 2015; Hawthorne & Kwan, 2012; Hess, 2009; Lattman et al., 2018; Ryan & Pereira, 2021; Ryan & Robinson, 2016; Van der Vlugt et al., 2019; Van der Vlugt et al., 2022). Subjective constraints, herein, encompass travel behavior and perception. Perception includes individuals' attitudes, affect, or feelings toward the physical environment, often expressed as ease, convenience, satisfaction, and overall experience with infrastructure, mode, and time usage during daily travel and activity participation (Jamei et al., 2022; Le & Carrel, 2021). A person's self-perceived abilities, travel willingness, and preferences are also considered subjective constraints that influence their evaluations of potential mobility (Pot, Van Wee, & Tillema, 2021). The consideration of both subjective and objective constraints makes perceived accessibility a lower estimate than the classic measures using objective constraints only, indicating an overestimation of the latter (Cheng & Chen, 2015; Kwan, 1999; Lattman et al., 2018; Lattman, Olsson, & Friman, 2016; Pot et al., 2021; Ryan & Robinson, 2016; Van der Vlugt et al., 2019).

Although existing literature extensively discusses the theoretical frameworks of perceived accessibility measures (De Vos, 2022; Dodge & Nelson, 2023; Pot et al., 2021), in most cases, they suffer from data and method limitations to fully operationalize their concepts. Most studies in this area rely on primary data collected through interviews and telephone surveys and apply statistical methods to summarize travel perceptions and accessibility for socio-economic communities residing over large geographic spaces (Jamei et al., 2022). In one way, these perceived accessibility measures advance traditional place-based approaches by highlighting differences in potential mobility as perceived by diverse socio-economic communities, which classic measures for the entire population cannot capture (Lattman et al., 2018; Pot et al., 2021; Ryan & Pereira, 2021; Van der Vlugt et al., 2019). However, existing perceived access measures can still be an overestimation, as their limited primary data does not allow them to capture the spatial-temporal variabilities in perceptions across road environments and activity locations that people encounter during their daily travel.

Few studies incorporate travel perceptions into time-geographic person-based access measures (Kwan, 1999; Kwan & Ding, 2008). Despite their preciseness in capturing the spatiotemporal variabilities in individual-level travel perceptions, these individual-level perceived access measures may contain uncertainties because they are less representative of broader socio-economic communities and thus unable to reflect the social differences in potential mobility. Additional research is needed to make the person-based measure scalable, representative, and appropriate for adoption in practice.

2.3. Inclusive accessibility

We propose the concept of inclusive access to further advance existing perceived accessibility measures. The inclusive accessibility concept integrates the spatial-social variations in perceptions into accessibility measures for individuals and communities. The inclusive accessibility concept classifies accessibility constraints into hard and soft constraints (Kar, Le, & Miller, 2023). The hard constraints are nonnegotiable physical and objective constraints imposed by our surrounding spatio-temporal environment, such as spatial distribution of facilities, personal travel time budget, and availability of road infrastructure and transportation services. Individuals must comply with these non-negotiable factors to make a trip and participate in activities. The soft constraints, on the other hand, are subjective and perceptual, also implicitly embedded in space and time. Examples of soft constraints are travel willingness, safety perceptions, and network and time preferences. While these factors do not directly impede individuals from traveling, they indirectly impact individuals' day-to-day travel decisions.

We conceptualize inclusive access as a subset of classic access. As mentioned, the classic accessibility measure evaluates a traveler's physical ability to reach places. It identifies the geographic coverage from where any traveler can reach the nearest opportunity locations, given their fixed travel time budget and spatial and temporal limitations of transportation services and activities. Inclusive accessibility takes a step further by taking into account the variations in access across space, among socio-economic groups and their travel perceptions. In this sense, inclusive accessibility evaluates both the physical and perceived ability of a traveler of certain socio-economic characteristics to reach opportunities. The geographic coverage, identified by inclusive access, thus indicates the area from where any travelers of the specified socio-economic community are physically and perceptually capable of reaching the nearest opportunity locations, given their hard and soft constraints.

Using a mobility survey dataset conducted in Columbus, OH, our previous study discusses the person-based inclusive access measure (Kar et al., 2023). This person-based measure successfully highlights the heterogeneities in travel perceptions across individuals. Yet, similar to previous person-based perceived access measures, it has certain data and modeling limitations, such as expensive data requirements and unknown transferability of one person-based model in predicting accessibility for another person (Kar et al., 2023). Most importantly, analyzing soft constraints and inclusive access at an individual scale makes it less appropriate for large-scale planning practices. Addressing the limitations of prior work, this paper advances the inclusive access measure by aggregating it across socio-economically diverse communities.

Another important contribution of the inclusive access measure lies in tackling the perception data limitations using ML prediction algorithms to ensure comprehensive data coverage of the soft constraints. Existing perceived accessibility research mostly relies on primary data collection and statistical modeling approaches, mainly different forms of descriptive statistics and discrete choice models. These statistical models are highly interpretable but require rigid assumptions about data distribution and produce flawed outputs in cases of multicollinearity, endogeneity, and unobserved heterogeneity (Hagenauer & Helbich, 2017; Zhang, Li, Pu, & Xu, 2018). In recent years, machine learning (ML) classifiers/regressors (e.g., decision tree-based models, support vector machines, and neural networks) have become popular in predictive travel behavior modeling as they are free of such rigid assumptions (Hagenauer & Helbich, 2017; Koushik, Manoj, & Nezamuddin, 2020; Ramírez, Hurtubia, Lobel, & Rossetti, 2021; Zhao, Yan, Yu, & Van Hentenryck, 2020). Despite being a black box with low interpretability, ML models support high prediction ability as they compute the intricate non-linear relationship between dependent and independent variables (Hagenauer & Helbich, 2017; Zhang et al., 2018). However, most of the past research using ML is focused on predicting mode choice, route choice, activity generation, and scheduling (Hagenauer & Helbich, 2017; Koushik et al., 2020; Zhao et al., 2020) where we find very few studies using ML to predict travel perceptions (Li, Jin, Sun, Jia, & Li, 2022; Ramírez et al., 2021). In this study, we leverage ML to predict individuals' walking perceptions and demonstrate a mechanism to use that knowledge to model accessibility across social groups.

2.4. Ensemble modeling

Ensemble modeling is an ML-based technique where multiple models are combined to make more accurate and robust predictions by leveraging the diversity and collective intelligence of the individual models (Wu & Levinson, 2021). Ensemble modeling follows a two-step process. First, we design multiple base models (e.g., random forest, support vector regressor), known as weak learners, because they make predictions that may be only slightly better than a random guess. In the next step, an aggregation algorithm, either deterministic (e.g., majority voting or averaging) or model-based (e.g., through a classifier/regressor), combines the weaker learners into a strong meta-learner for more accurate predictions (Cheng et al., 2020; Wu & Levinson, 2021). Thus, ensemble modeling provides a mechanism to generalize multiple weak learners into a stronger one to minimize variance and improve model performance (Mendes-Moreira, Soares, Jorge, & Sousa, 2012; Wu &

Levinson, 2021; Wu, Zhang, Jiao, Guo, & Alhaj Hamoud, 2021). Depending on data properties and modeling criteria, ensemble models can be heterogeneous (i.e., different classifiers/regressors for the base models and meta-learner) or homogenous (i.e., the same classifiers/regressors for all models).

Ensemble algorithms are of three types: bagging, boosting, and stacking. Both bagging and boosting are examples of homogenous ensembles, whereas stacking can accommodate both homo- and heterogeneous. A key difference among these variants lies in the data subsetting mechanism for the base learners and aggregation algorithm. A bagging ensemble (e.g., random forests) uses a subset of datasets with replacements to train the base learners and aggregate them through majority voting or averaging (Breiman, 2001). A boosting algorithm (e.g., adaptive and gradient boosting) initiates the model training with a random subset and then continues reweighting the parameters of the models in a sequence, with emphasis on misclassified instances (Schapire, 1990). In a stacking ensemble, the data is divided into *k*-subsets, and the base models are trained iteratively by fitting them on *k*-1 folds and making predictions on the remaining fold. After training the base models, the collected predictions are used to fit the meta-model, which aggregates the outputs of the base models to make the final prediction (Wolpert, 1992). The stacking generalization is sometimes termed a blending ensemble when a hold-out validation dataset is set aside instead of using out-of-fold prediction to generate input features for the meta-learner (Wu et al., 2021).

Wu and Levinson (2021) outline two major applications of ensemble models in transportation research: 1. Combining multiple models to overcome the limitations and uncertainties involved in single model assumptions and 2. Combining data to generalize information from multiple sources. Irrespective of the categories, ensemble models are widely applied in past transportation research on mode choice and ride-sharing behavior (Chen, Zahiri, & Zhang, 2017; Cheng et al., 2020), trip purpose (Ghasri, Hossein Rashidi, & Waller, 2017), mode-specific traffic flow (Jin et al., 2020; Li, Yabuki, & Fukuda, 2022), activity-based travel demand (Hafezi, Daisy, Millward, & Liu, 2021), driving style (Bejani & Ghatee, 2018; Xing, Lv, Wang, Cao, & Velenis, 2020) and crash severity (Ji & Levinson, 2020).

3. Data

Our study area is Columbus, Ohio, USA, where we conducted a mobility survey to collect individual-level data on daily travel patterns and experiences. We obtained the following travel perception data from each traveler during the mobility survey.

3.1. Street-specific perception data

We asked participants to rate different Columbus streets based on their perceptions of safety, comfort, and willingness to walk within those road environments. We used a Likert scale of strongly disagree (1) – strongly agree (5), and three statements for rating each street: *"I am willing to walk on this road", "I feel safe from crashes when walking on this road",* and *"The surrounding environment is pleasant."* We use this information as soft spatial constraints in this study.

3.2. Travel-time preference

We also asked participants to state their preferred travel time for transit rides and walking trips by purpose, assuming that the street designs fulfill their network preferences and safety perceptions. We use this information to represent soft temporal constraints.

3.3. Personal information

We also collected data on participants' socio-economic status (SES) (gender, income, and race) to define our social groups.

The main task of the survey was to rate different streets of Columbus, which can be tedious. Hence, we designed the survey in three steps to account for the high attrition rate during the survey procedure. Once a participant entered the online baseline survey, we showed Google Street Views (GSV) of 20 representative roads in Columbus and asked them to rate each street based on their perceptions of safety, comfort, and walking willingness. Participation in the next two steps was voluntary. In the second step, the pop-up survey, participants tracked their trips for a week using the ArcGIS field maps mobile app, took 40 street photos on their route, and rated them using the same indicators. In the end survey, participants rated an additional 40 Google Street Views of Columbus roads.

We compensated the participants after each survey completion to encourage participation in the next step. Participants received compensation of $10 and $15 for an approximate time commitment of 30 and 60 min in the baseline and end surveys. The compensation for pop-up surveys was $30 for 80 min of active participation to complete the photo surveys and 7 days of inactive mobility tracking through the app. Moreover, we excluded participants who completed the baseline survey in less than 10 min to ensure reliable and sincere online survey responses.

We have 477 participants who completed the baseline survey. Of these, 40 completed the pop-up survey, and 237, including the participants in the pop-up survey, completed the end survey. The rest (240 travelers) only completed the baseline survey. Despite the compensation, the survey medium perhaps played a role in the unequal survey participation rates. Participation was higher in the baseline and end surveys as they were easier to complete online compared to the pop-up surveys involving active outdoor engagements.

We collected secondary data sets on the existing road infrastructure and the built environment (Table 1). We use these datasets as input for modeling and predicting soft constraints.

4. Methods

The first step of designing inclusive access is to measure network-specific soft constraints for 12 mutually exclusive social groups. We define these social groups based on travelers' gender (male and female), annual income (low: $\leq$ $45,000, high $\geq$ $75,000, and moderate: $45,000 - $75,000), and race (white and people of color). Table 2 provides the total number of survey respondents in each social group and the number of them completing two or more surveys. We use this categorization later for data splitting.

Most previous studies quantify perceptions as an index, averaging several subjective factors such as self-perceived ability, ease,

Table 1
Additional land use and transportation network data used in this study.

Variable	Data type	Source
Number of lanes	Continuous	Mid-Ohio Regional Planning Commission (MORPC)
Posted speed limit (miles per hour)	Continuous	
Functional class, excluding interstates, freeways, and ramps	Categorical	
Road width (meters)	Continuous	Federal Highway Administration, USDOT
Average daily traffic volume	Continuous	StreetLight Data Inc.
Sidewalk availability	Binary	
Sidewalk width (meters)	Continuous	Mid-Ohio Regional Planning Commission (MORPC)
Buffer zone	Binary	
ADA Compliance of sidewalks	Binary	
Concrete surface of sidewalks	Binary	
Light and dense vegetation within a 10-m buffer from the street centerline, estimated using NDVI measures on Landsat 8 data (in square meters)	Continuous	United States Geological Survey (USGS)

Table 2
Total number of survey respondents in each social group and the number of them completing two or more surveys.

	High-income		Moderate-income		Low-income	
	Total	**Completed two or more surveys**	**Total**	**Completed two or more surveys**	**Total**	**Completed two or more surveys**
White-men	12	5	22	16	56	31
Men of color	2	2	9	7	69	41
White-women	52	13	52	23	96	47
Women of color	6	2	16	10	85	40

satisfaction, and willingness to travel and activity participation (Lattman et al., 2016, 2018; Van der Vlugt et al., 2019; Van der Vlugt et al., 2022). Similarly, we estimate soft constraint as a composite walking perception score of a certain street – by averaging the ratings of walking willingness, perceptions of safety, and comfort from each traveler. Note that the survey dataset only contains traveler-specific walking perception scores for a selected set of Columbus streets. We apply an ensemble algorithm on the survey dataset to predict walking perception scores for the rest of the streets in the network separately for each social group. The output of the prediction model is the estimated street-specific walking perception score for a social group with values ranging from 1 to 5, where a high value indicates that a traveler belonging to that social group considers the street highly walkable. The input features are road and land use characteristics (variables shown in Table 1) and socio-demographic information (age, gender, and race). We perform one-hot encoding for the categorical input features to convert them into multiple binary variables and min-max scaling of 0–1 for the continuous features.

For each street surveyed by a traveler, the information collected can be organized as a pair of input feature vector and its associated target value. The input feature vector (x_1, …, x_{11}, gender, income, race) contains attributes of a street shown to a traveler in the respective survey (x_1 through x_{11}, as shown in Table 1) and the socio-economic characteristics of the person (gender, income, and race). The target value is the walking perception score given by the traveler. A key characteristic of our survey dataset is that each participant rated the same set of 60 streets during the baseline and end survey. The input feature vectors are identical for these streets with varying output values when they are rated by travelers with the same socio-demographic characteristics. For example, the input feature vector for a certain street in the baseline survey is the same for two travelers who are both women, low-income, and people of color. However, the target values (walking perception scores) given by these two travelers may differ based on each person's perception. Given our unique data characteristic, traditional prediction algorithms may be unable to effectively learn the underlying pattern in the dataset, leading to high model complexities, high prediction errors, and potentially poor generalization performance on unseen data (Bishop & Nasrabadi, 2006; Gudivada, Apon, & Ding, 2017).

Ensemble modeling can overcome the limitation with identical feature vectors by modeling and combining the results across data subsets collected from multiple sources (Wu & Levinson, 2021), in our case, survey responses from multiple travelers. This study adopts an ensemble model partly modified from stacking and blending generalization. In this process, we first systematically split part of the survey data into traveler-specific training data subsets and use the rest as validation and test sets to avoid repeating the same road in the input datasets. Next, we model traveler-specific walking perception scores and then generalize the predictions across social groups using the training, validation, and test sets. This data-splitting process, followed by the modified ensemble, enables hierarchy in the modeling process and supports our research objective of person-to-group level generalization of soft constraints (Jin et al., 2020; Wu et al., 2021).

4.1. Data splitting

We split the entire survey data into training, validation, and test sets to omit repetition of the same roads in each input dataset. Fig. 1 illustrates the data-splitting mechanism adopted in this study. The training set contains baseline and end survey data that are completed by the 237 travelers. We further classify the training set into 237 traveler-specific data subsets, where each subset contains responses on 60 streets used in the baseline and end survey. As we will discuss later in this section, each subset is used to train a base model in the ensemble, which effectively avoids the use of identical streets in the input of the model. The validation dataset contains pop-up survey data completed by 40 out of the 237 travelers, consisting of 1600 unique roads (40 streets rated by 40 travelers) chosen and rated by these travelers during the pop-up surveys. We use the validation set to aggregate the base models by fitting a meta-learner. The output in the training and validation set contains scores provided by the travelers on these unique road datasets, and the input feature set represents corresponding road and travelers' characteristics.

The test set contains data from the 240 travelers who only completed the baseline survey and did not proceed further. There are 4800 (20 streets rated by each traveler) data records in this set. We use the test set to evaluate the performance of ensemble models in predicting walking perception scores for a new traveler. Since each traveler in the test set only rated 20 street photos, individual base models on these small-size data would be unstable and inaccurate. Nonetheless, their responses can serve as a reference to test how well the ensemble model performs in predicting walking perception scores for anonymous travelers. Therefore, test data input and output represent the baseline survey roads, socio-economic attributes of 240 travelers, and their walking perception scores for those roads.

Given that travelers are unevenly distributed across 12 social groups (Table 2), we ensure to have representative participants from all groups during the model development process to account for their travel perceptions. However, due to its relatively small size, our test dataset does not contain any travelers from the group of high-income men of color. Therefore, our model performance scores, estimated as an average for all groups, may not entirely reflect the ensemble model's effectiveness in predicting walking perception scores for this group.

4.2. Model specifications

The general procedure (Fig. 2) of our modified ensemble is to: (1) fit the base models using the traveler-specific training dataset, (2) make predictions from the trained base models using the validation set, (3) fit a meta learner considering the base model prediction as input and the target values in the validation set as output, and (4) evaluate the performance of the modified ensemble using the test set. We design three ensemble models using three different types of regressors, namely random forest (RF), support vector regressor (SVR), and neural network (NN). We choose these models because of their wide range of applications in transportation research (Hagenauer & Helbich, 2017; Koushik et al., 2020; Ramírez et al., 2021; Zhao et al., 2020). Each ensemble uses homogenous base models and the meta-model (e.g., the SVR ensemble fits SVR regressors for all base models and meta-model). In each ensemble, we independently tune the hyperparameters for base models and meta-model - a common hyperparameter tuning approach for ensemble models (Shahhosseini, Hu, & Pham, 2022). The hyperparameter tuning process uses random search-based 5-fold cross-validation and mean squared errors as evaluation criteria for a given

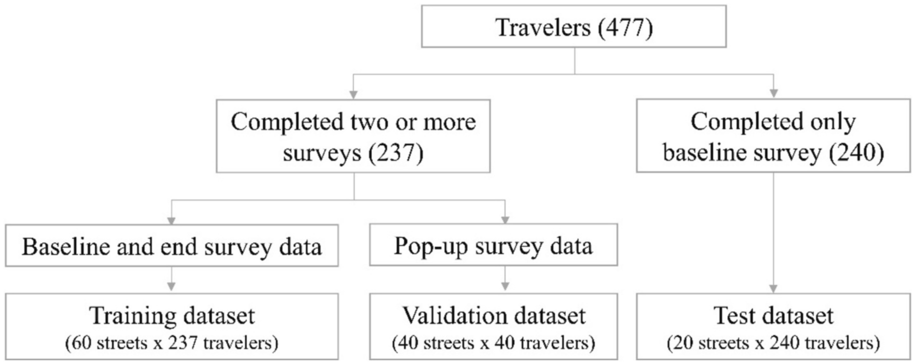

Fig. 1. Data splitting process for the modified generalization ensemble.

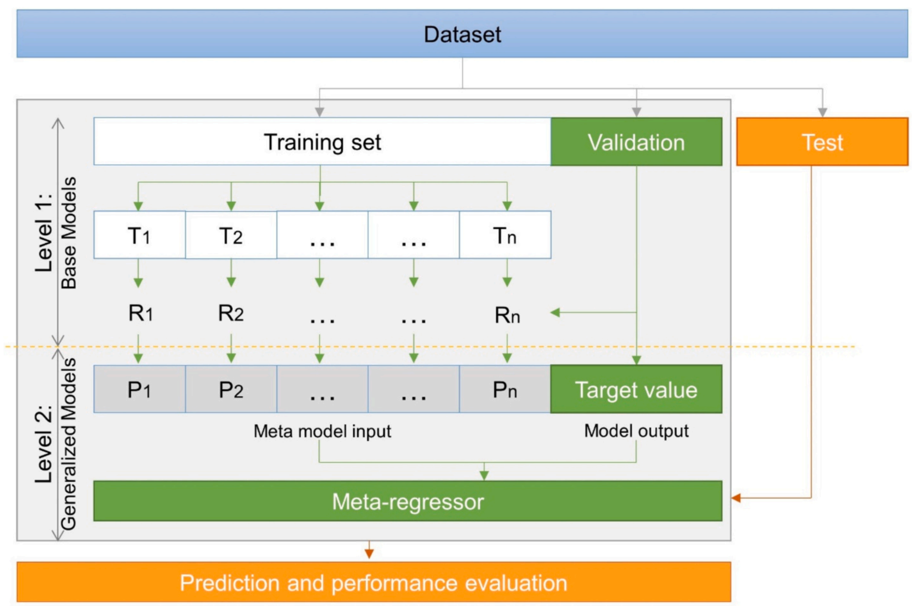

Fig. 2. Workflow of modified generalization ensemble. R_1 through R_n represents the base models fitted using traveler-specific training dataset T_1 through T_n, where n is the number of travelers in the training set. P_1 through P_n are the predictions made on the validation set using respective base models.

regressor and its corresponding search space, including a range of possible hyperparameter values.

The RF, SVR, and NN-based ensemble models are implemented and tested separately. In addition to the three ensemble models, we use the respective traditional regressors as alternate benchmarks to compare performance. For the traditional models, we use training and validation datasets for model training and testing set for performance evaluation. Finally, we choose the model with the best mean absolute error (MAE) and mean squared error (MSE) scores to predict group-specific walking perception scores and apply the estimates in measuring inclusive access.

In RF-ensemble, the hyperparameter search space includes the number of trees (200–2000), maximum features (auto, sqrt), maximum depth (10–100), minimum samples split (2–10), minimum samples leaf (1–4), and bootstrap (Breiman, 2001). In the SVR ensemble, the search space contains a Radial Basis Function (RBF) kernel and different combinations of Gamma (0.001–0.5), C (0.001–0.1), and epsilon hyperparameters (0.01–100) (Smola & Schölkopf, 2004). Lastly, in NN-ensemble, the neural network is considered a sequential architecture containing two hidden layers with dropout regularization between each layer. The search space of NN ensemble is designed with different combinations of hyperparameters: number of neurons for each hidden layer (10–200), initial weights (uniform, zero, normal distribution), activation functions (relu, tanh, sigmoid, linear), dropout rate (0–0.4), optimizer (Adam or SGD) (Shahhosseini et al., 2022). The values in the parentheses represent ranges used for tuning respective hyperparameters. We also use the same search space, hyperparameter tuning process, and evaluation criteria for the corresponding traditional RF, SVR, and NN models to maintain consistency.

4.3. Design of base models

Our ensemble algorithm fits the base learners to each traveler-specific training data subset $\{T_1, T_2, \ldots, T_n\}$, where n ($n = 237$) is the number of travelers contributing to the training data set. In other words, there are 237 base learners, and each of them is trained using the data from a unique traveler, which consists of 60 streets. Each base learner, therefore, models the walking perception scores of the respective traveler, considering the street characteristics and their socio-demographics. For each traveler-specific training data subset T_i ($1 \leq i \leq n$), we tune hyperparameters and fit base model R_i. As mentioned earlier, these base models are homogenous (e.g., all base models are SVRs in the SVR ensemble). Additionally, we use the input data from the validation set to make predictions P_i from R_i. Here, P_i is a set of walking perception scores predicted for the new roads in the validation set using base model R_i. At the end of this process, we get a set of traveler-specific base models, $\{R_1, R_2, \ldots, R_n\}$ and corresponding validation set predictions $\{P_1, P_2, \ldots, P_n\}$.

4.4. Design of generalized model

The generalization procedure assigns weights to the base models based on their performance in predicting the walking perception score of the new roads in the validation dataset. This generalization process fits the meta-model using the same type of regressor as in the base models, the base model predictions on the validation set $\{P_1, P_2, \ldots, P_n\}$ as input, and the target values from the validation set as output.

4.5. Evaluating model performance

This step evaluates the performance of the ensemble model in predicting walking perception scores for the new travelers in the test set, whose data are not used in the modeling process. In this process, we pass input data from test set through each base model R_i $(1 \le i \le n)$ to get predictions of walking perception scores from all base models. Next, we use these base model predictions on test set as input for the fitted meta-model to make final predictions. Lastly, we estimate MAE and MSE between ensemble predictions and actual responses in the test set.

4.6. Classic and inclusive accessibility measures

The ensemble models allow us to compute a walking perception score for each socio-economic group for each street in our study area. We consider these scores a representation of soft constraints in measuring inclusive access. Additionally, we consider a maximum travel time budget, sidewalk availability, and public transit schedule hard constraints. With these hard and soft constraints, we then calculate classic and inclusive access to food stores for each group. Following the criteria set by Kar, Carrel, Miller, and Le (2022), we define food stores, mainly as large-scale supermarkets, warehouse clubs, and departmental stores (e.g., Walmart, Kroger, Target, Costco, and Sam's Club) that are more likely to carry fresh and wide assortment of produces compared to other local grocery stores, discount, and convenience stores. We use 30 min as a fixed travel time budget following past research investigating food access using public transit in the United States (Kar et al., 2022; Widener, Farber, Neutens, & Horner, 2013).

The classic accessibility measure identifies all space-time locations along a transportation network from where any traveler, regardless of their social status, can start a trip and reach a nearby opportunity location within a specified travel time budget. Particular to this study, we delineate classic accessibility as the network space from where any traveler is physically capable of reaching the nearest food stores by using public transit and walking within the travel time budget of 30 min, and starting their trip at 8 AM on a regular weekday (Tuesday).

To further compare between classic and inclusive access measures, we design two types of inclusive access: inclusive access with soft spatial constraints (inclusive access 1) and inclusive access with soft spatial and temporal constraints (inclusive access 2). The first inclusive access considers all hard constraints of classic access mentioned above, as well as walking perception scores of social groups as soft spatial constraints. To do this, we first modify the road network to eliminate the streets with low walking perception scores (walking perception score ≤ 3) for the respective group. Using this modified road network, inclusive access 1 for a social group identifies the network space that any traveler from the respective group perceives as accessible as well as they can physically reach the nearby food locations within the 30-min travel time budget. The second inclusive access modifies the first one by considering the travel time budget as a soft constraint instead of a hard one. Here, we estimate the preferred transit and walking time for each social group by applying the majority rule on individual-level travel time preference data. Instead of a fixed time, we use this mode-specific travel time preference as the travel time budget to delineate inclusive access 2 for a social group.

5. Results

Once both classic and group-specific inclusive access measures are estimated, we explore how the inclusive accessibility measure varies across social groups that cannot otherwise be captured by the existing classic accessibility measures. We quantify the differences in classic and inclusive access for each social group in two ways. First, we estimate the length of the road network covered by the classic and inclusive accessibility and then calculate the proportion of classic access network that also falls within the network coverage of inclusive access 1 and 2. Next, we also calculate the number of food stores accessible by both inclusive measure and their percentages compared to the classic one.

5.1. Model performance

Fig. 3a and b provides the MAE and MSE scores on the test set estimated from the traditional and ensemble models. Overall, the MAE scores for all models are below 1, which we consider an acceptable threshold for model performance. Since the original Likert scale in the survey contains five scores, with a unit difference between each score, MAE values less than 1 indicate that, on average, the model predictions do not shift more than one scale from the original data. Also, the ensemble approach improves model performance for all cases except for the neural network. One possible reason for the worst performance of neural networks is their inherent need for a substantial amount of data, in contrast to our base models developed using small training data subsets. We use the SVR ensemble for further analysis of inclusive access as it outperforms other traditional and ensemble models in terms of both MAE and MSE.

5.2. Differences in soft constraints across groups

The SVR ensemble model estimates walking perception scores as soft spatial constraints for all social groups and all Columbus streets except highways and freeways. Fig. 4 provides some examples of group-specific walking perception scores predicted for high-income white men, moderate-income women of color, low-income men of color, and low-income women of color. The maps use a red-to-green color scheme to represent roads perceived as the least and most walkable. The results show substantial variations in people's perceptions of a walkable environment depending on their gender, race, and income. High-income white men find most Columbus streets moderate to highly walkable. Note the streets where this population group feels indifferent (marked in yellow), moderate-income women of color find those streets unfavorable for walking trips (marked in oranges). Again, most streets in southeast Columbus yield higher barriers to low-income people of color regardless of gender (marked in yellow to red). However, like other groups, low-income men of color find the southwestern part of Columbus highly walkable (marked in dark green), which is not the case for low-income women of color (marked in light green). Interestingly, the walking perception maps of the low-income population resemble the high-injury networks and pedestrian crash hotspots of Columbus, mapped by the Columbus Vision Zero initiative (Vision Zero Columbus, 2021).

Fig. A1 in the appendix further illustrates the similarities in walking perception scores among these four example groups. These groups share similar perceptions of walking (marked in orange) for the streets in central Columbus, primarily downtown, but different views (marked in grey) in the northwest and southeast directions. Despite the difference, perceptions of streets in northwest Columbus, especially its outer suburbs, are mostly positive (score 4 or 5), with all groups finding them acceptable to varying degrees (Fig. 4). Conversely, perceptions of streets in southeast Columbus are mostly negative, especially among low-income communities who find the roads unsuitable for walking, while high-income communities identify them as somewhat walkable (Fig. 4).

Social differences in daily travel patterns and exposure to specific

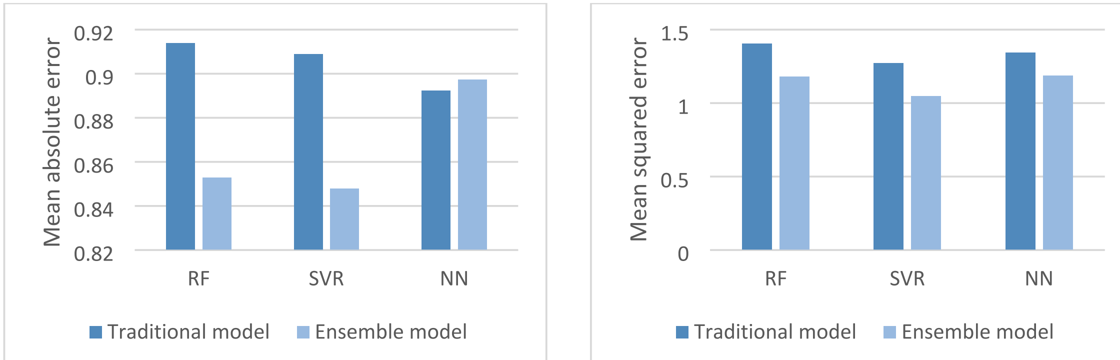

Fig. 3. a) Mean absolute errors (MAE) and b) mean squared errors (MSE) of traditional and ensemble models for predicting perceived walkability scores

travel environments may have contributed to such perceptual differences. Nearly all social groups visit Downtown Columbus for utilitarian and recreational purposes, fostering equal exposure, awareness, and consensus among groups. In contrast, northwest and southeast Columbus, as high- and low-income areas, respectively, experience infrastructural disparities, with the southeast being served less. The disagreements in perceptions of southeastern streets possibly stem from low-income communities being more exposed to these poor conditions and thus expressing greater concern.

Using the SVR ensemble, we predict walking perception scores for the 12 mutually exclusive social groups. Fig. 5 shows the percentages of Columbus streets (in length) perceived as walkable (score 4 or 5) for each group in both absolute terms and relative to the walkable travel environment of the high-income white men. Overall, the absolute percentage ranges between 53 and 62 %, indicating that travelers find approximately half of Columbus streets non-walkable. Notably, both absolute and relative comparisons suggest that the perception of a walkable environment and mobility barriers depend more on travelers' income status than their gender or race. The percentage of walkable streets is the highest for high-income white men and gradually decreases with the decline of travelers' income. Men find more streets walkable than women in Columbus for all races and incomes, except for low-income white populations. Also, low-income and high-income people of color find fewer streets favorable for walking compared to their white counterparts.

5.3. Classic and inclusive accessibility measure

Fig. 6 provides the classic and inclusive access measured for our example social groups. The blue, green, and red colored road networks, respectively, indicate people's classic access, inclusive access 1 with soft spatial constraints, and inclusive access 2 with both soft spatial and temporal constraints. Note that the classic access for all social groups is the same, as it only considers the hard space-time limitations and disregards the effect of travel perceptions. Considering a 30-min travel time, availability of transit, and sidewalks, only half of Columbus streets, measured by classic access, provide access to the nearest food store. Compared to the classic measure, we observe noteworthy differences in geographic spaces that feel accessible to these groups, measured by their inclusive access. While high-income white men and moderate-income women of color residing in affluent neighborhoods of Columbus (e.g., central Columbus and the center of north-western suburban cities) can access the nearest grocery stores, low-income people living in the less-affluent eastern part of Columbus experience minimal access, considering inclusive access 1. The differences between inclusive access 1 and 2 are minimal for all groups except for moderate-income women of color.

Fig. 7 shows the proportions of classic access network that provides inclusive access for all groups. The network coverage drops substantially as we shift from classic access to the first inclusive access measure considering walking perception scores only. The difference between classic and inclusive access 1 is the highest for low-income people of color. The coverage of inclusive access 1 for this group is about 1/4th of the classic access coverage. Additionally, the coverage of inclusive access 1 is smaller for women than men, regardless of their income and race. We observe slight declines in accessibility while shifting from inclusive access 1 to inclusive access 2 with considerations of soft travel time preferences. This decline between inclusive measures 1 and 2 is substantial for moderate-income people of color due to their low-travel time preference for walking and transit rides.

Fig. 8 depicts the percentages of food store locations accessible by inclusive access 1 and 2. Since our measure of classic access is destination-focused, it searches for all food store locations accessible by public transit and walking. When considering soft constraints, most groups can access only about 1/3 of the food stores. This percentage is even lower for low-income people of color – only 1/4 of the food stores remain accessible. The decline in opportunity locations between inclusive access 1 and 2 is minor except for moderate-income people of color.

6. Discussion

6.1. Major findings and implications

The study introduces an inclusive accessibility concept and measure that captures differences in travel behavior for social groups. We design a novel data collection approach on individual-level mode-specific travel perceptions using GSV and ArcGIS field maps mobile app applied to 477 participants in Columbus, OH. We also develop a bottom-up approach to systematically include individual-level space-time limitations and travel perceptions in measuring accessibility over a large geographic space.

This study demonstrates a unique methodology that computes personalized travel perceptions and generalizes them into a group-based measure using an SVR ensemble approach. Travel behavior literature often discusses the influences of attitude, perceptions, and experiences in mode choice and travel decisions (Alfonzo, 2005; Ma & Cao, 2019; Singleton & Clifton, 2014). Undoubtedly, these attributes can reflect people's travel patterns and produce a more accurate and realistic accessibility measure (Kar et al., 2023). Yet, we do not see much application of these attributes in accessibility research as they are highly delicate and diversified, often difficult to quantify and integrate. This study overcomes that limitation and demonstrates a mechanism to model these heterogeneous travel perceptions by homogenous social groups with a low data requirement. The multilevel ensemble approach of soft constraints modeling enables computing individual- and group-level soft constraints. The data splitting mechanism in the ensemble allows us to examine how well each traveler-specific base model performs in predicting their walking perception scores in a different travel

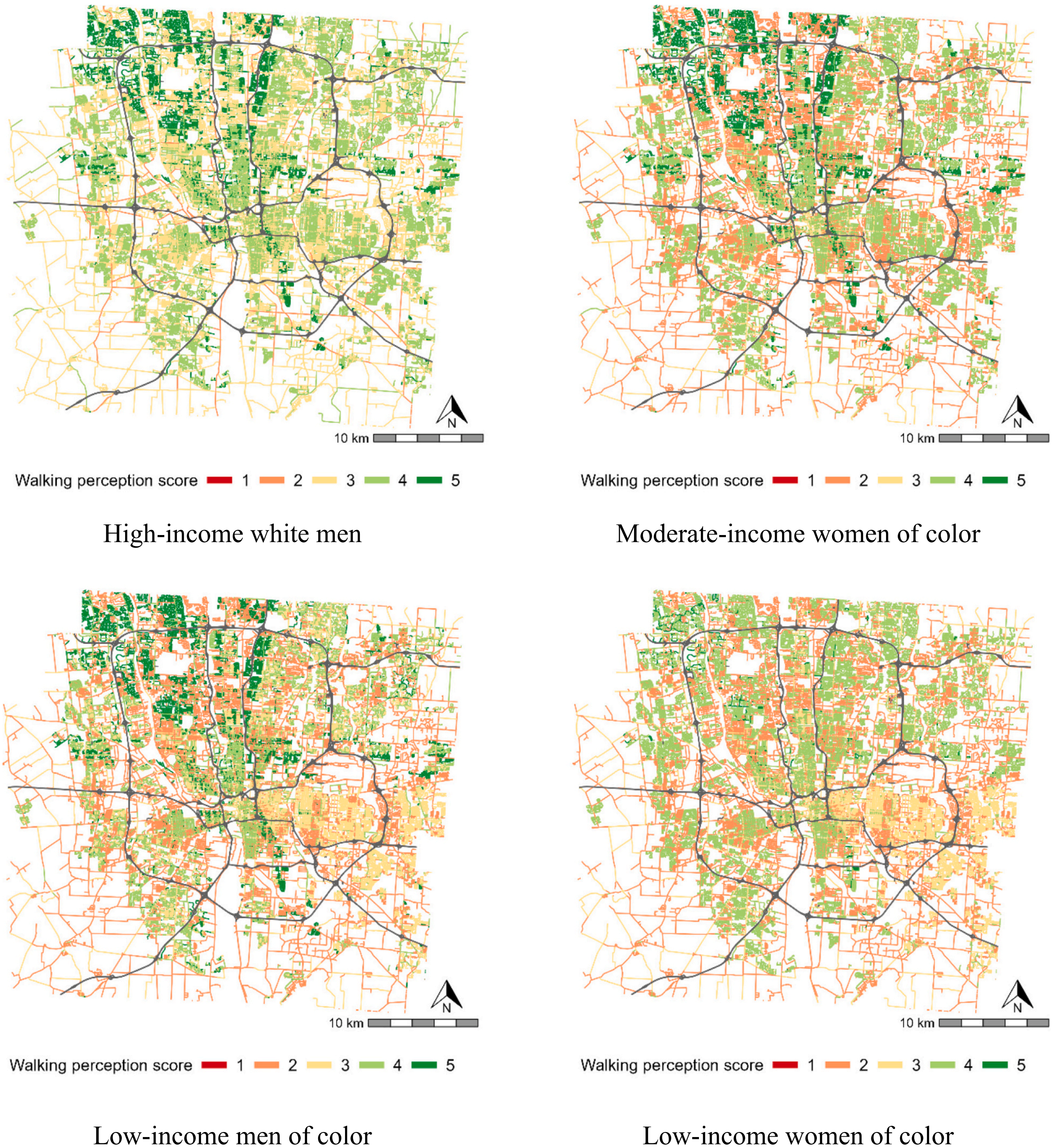

Fig. 4. Walking perception score predicted using support vector regressor ensemble for high-income white men (top-left), moderate-income women of color (top-right), low-income men of color (bottom-left), and low-income women of color (bottom-right).

environment, as well as how accurately the generalized model measures walking perceptions for new travelers.

The study highlights a major fallacy in our infrastructure design and current planning policies. The design of our road infrastructures mainly caters to the needs of people with advantages, privileges, and physical abilities. Indeed, these infrastructures do not yield equal access to everyone due to the diversity in peoples' travel needs and preferences for infrastructure and urban facilities. The study points to quantifiable discrepancies and provides evidence of how similar travel environments may yield different levels of impedance to people. Our results show that (physically able) high-income white men, a representation of the advantageous population, experience fewer mobility barriers than any other community. Meanwhile, economically and racially disparate communities recognize many parts of Columbus as problematic, which are also the high-injury and crash-prone areas of Columbus (Vision Zero Columbus, 2021). Our current planning practices are limited in accommodating these diverse risks and travel needs.

The social differences in safety perceptions, ideal travel environment, and overall sense of place are perhaps the derivatives of people's daily travel experiences, exposure, and awareness of the existing travel environment. Our study finds stark differences in group-specific travel perceptions in the southeast parts of Columbus, where residential segregation and socio-economic disparities are more pronounced. While high-income communities experience limited exposure to road risks within their residential neighborhoods, more than 30 % of pedestrian fatalities occur in low-income neighborhoods (Smart Growth America,

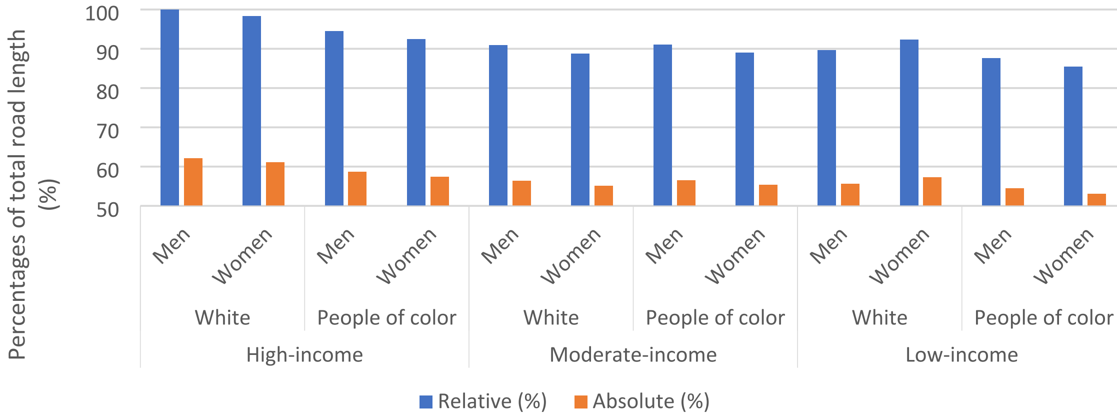

Fig. 5. Percentage of total road length perceived as walkable (score > 3) for all social groups and its relative comparison with high-income white men.

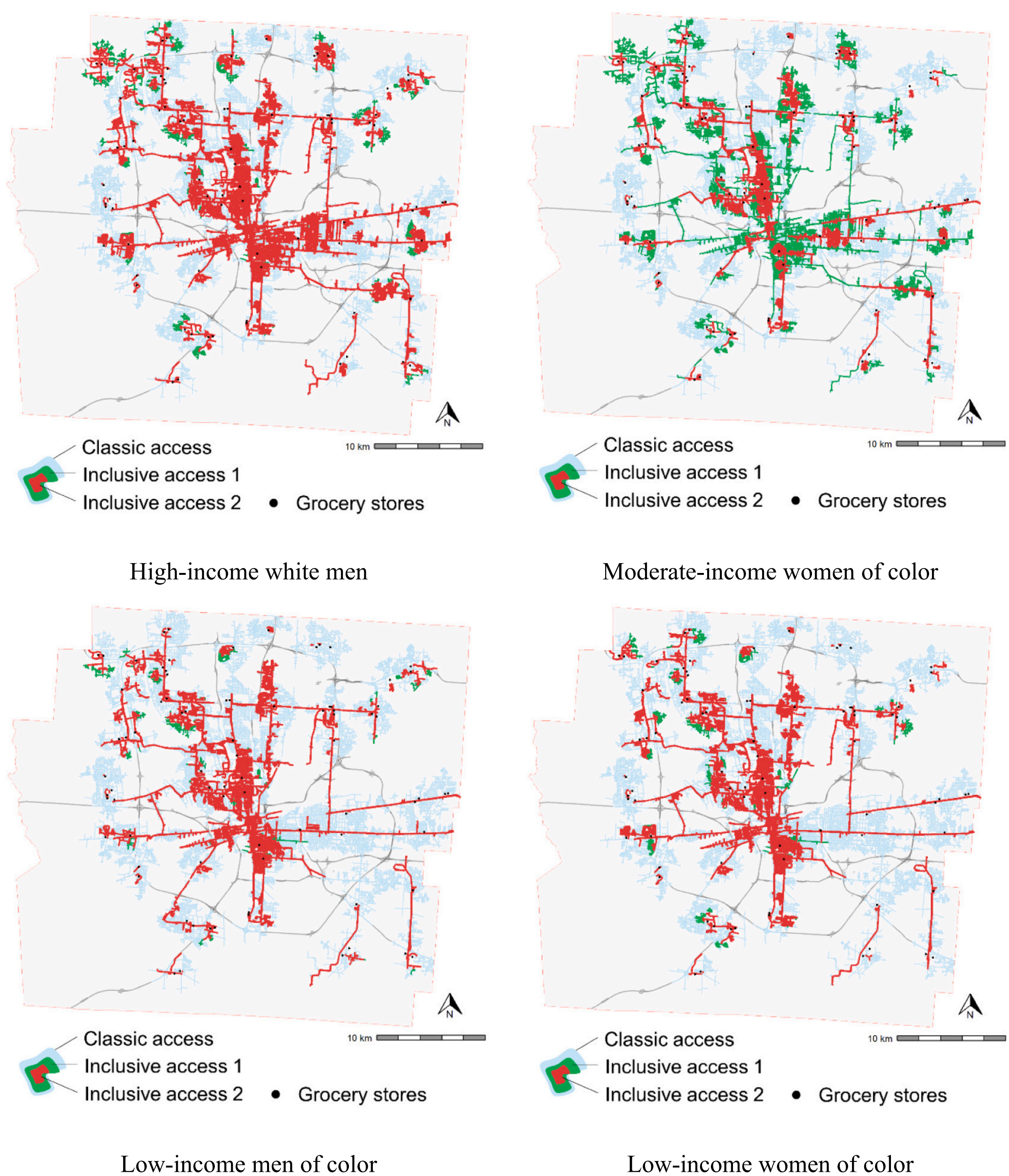

Fig. 6. The classic and inclusive accessibility estimated for the high-income white men (top-left), moderate-income women of color (top-right), low-income men of color (bottom-left), and low-income women of color (bottom-right).

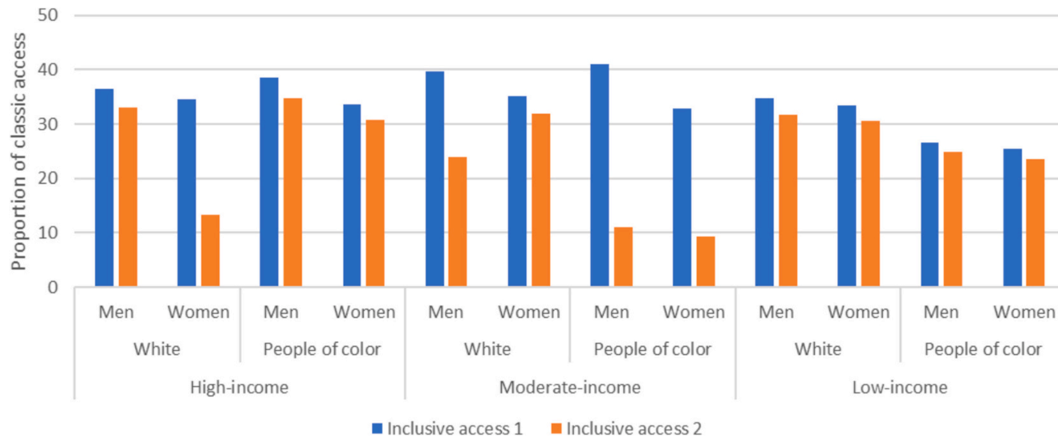

Fig. 7. Proportions of road network accessible by inclusive access measure compared to classic access.

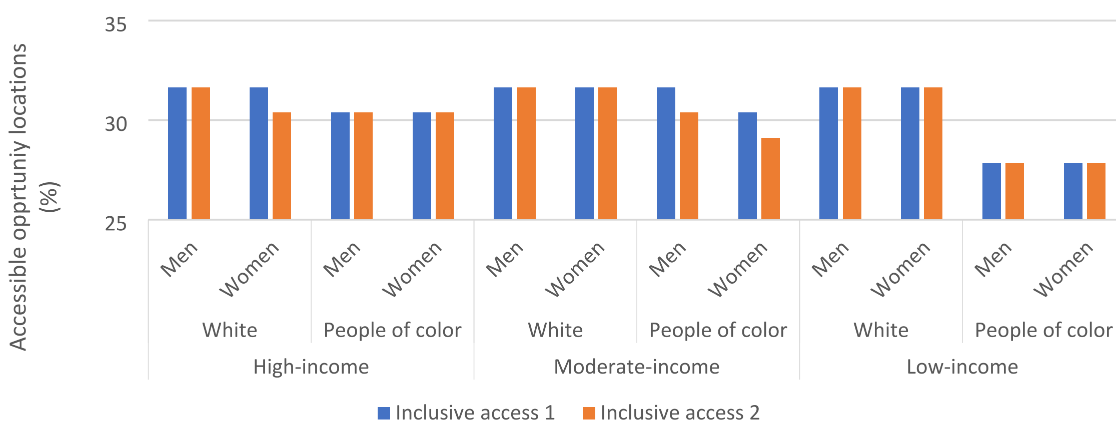

Fig. 8. Percentages of food store locations accessible considering the inclusive access measure.

2022), such as those in southeastern Columbus. This greater exposure to direct and indirect road violence and traffic trauma makes low-income communities more aware and fearful of the flaws in the travel environment. Therefore, the perceptual differences across income groups stem from low-income communities finding themselves in more vulnerable and life-threatening situations, compared to high-income communities feeling more secure and comfortable within existing walking environments.

Our study is also unique in introducing mode-specific travel time as a soft constraint and its variations across communities. The results show that moderate-income people are unwilling to take longer transit rides and/or walking trips compared to low- and high-income populations. We explain these varied travel time preferences as a trade-off between how communities value their travel time and how time-poor they are. Usually, the value of travel time increases while time poverty decreases with income and affordability (Athira, Muneera, Krishnamurthy, & Anjaneyulu, 2016; Whillans & West, 2022). Even if we provide moderate-income people with their ideal walking environment, they are reluctant to switch to alternate travel modes for longer travel since they are time-poor and can afford to use cars. However, that's not the case for low- and high-income communities since the former group cannot afford to spend more to save travel time, and the latter aren't time-poor. These findings clearly indicate who needs transportation services more, whose travel preferences should be prioritized, and where the investments should be.

The study overcomes the limitations of person- and place-based accessibility measures (Kwan & Weber, 2008; Miller, 2007). The classic access measure, a representation of a place-based approach, delineates the same outputs for any population group residing within the same geographic space. The inclusive access measure overcomes such place-based fallacies by incorporating travel behavior differences across communities. The study exemplifies that our built environment and time budgets do not only impose physical barriers; they can also create perceptual and psychological barriers, impeding travel and activity participation. These soft spatial and temporal constraints again vary across individuals and social groups residing within the same geographic space. The person-based measures, although highly effective in capturing the complex relationship between travel perceptions and accessibility, can be quite ineffective and impractical for real-life interventions. This person-based to place-based translation thus allows inclusive accessibility measures to be applied in network design and transportation planning with consideration of the social differences in travel choices and accessibility.

6.2. Study limitations and future directions

This study has certain limitations and scope for future advancements. The study participants are chosen randomly for the mobility survey, leading to an unequal number of sample participants in each social group. The sample dataset from the social groups with a higher number of travelers may dominate our prediction of walking perceptions. Moreover, due to the limited number of sample travelers, we evaluate model performance in an aggregated manner that does not account for varying prediction accuracy across different socio-economic groups. Future research may adopt more systematic and stratified sampling approaches to ensure a representative sample of participants from all demographics and socio-economic groups of all Columbus neighborhoods. This method will guarantee a proportional distribution of all social groups within the sample, leading to a more accurate prediction and separate group-specific evaluation of model performances. Our survey questionnaire is also limited in capturing travel choices and perceptions of people with physical and mental disabilities. An extension of this data collection can be designed, particularly for capturing mode-specific travel perceptions for people with mobility disabilities.

Moreover, future studies may advance the survey design to reduce self-selection biases and anchoring effects. Our survey dataset may contain self-selection biases as those who opted for the mobile app survey part may be more attuned to their travel patterns and perceptions, which may lead to overestimation in the models. Also, travelers' survey responses may have some anchoring effects, wherein their preconceived preferences and biases toward certain neighborhoods in Columbus may affect their responses regardless of the actual infrastructure present in those areas. To address these limitations, future data collection efforts may provide additional instructions to the participants to be aware of their pre-existing opinions and biases while responding. Instead of using real-world street photos, they may also utilize simulated street photos or virtual reality that depict different combinations of road amenities and the surrounding built environment. By doing so, researchers can minimize anchoring effects in survey responses more effectively, as respondents would not be influenced by their prior knowledge or associations with specific locations.

Future studies may also enhance the modeling of soft constraints and inclusive access in several ways. For instance, the existing estimations of walking perception scores assume equal weights for the perception indicators - safety, comfort, and willingness. However, the importance of each indicator in shaping walking perceptions may differ across socioeconomic groups, such as low-income people prioritizing safety over comfort. Future research may test different weighting schemes of each perception indicator for each social group to yield a more accurate walking perception measure.

Similarly, our inclusive accessibility measure treats the walking perception score as a binary constraint, assuming people only walk when the travel environment seems favorable. In other words, a route is excluded from the inclusive accessibility measure if any link on that route feels unwalkable to the traveler. To further accommodate people's varying tolerance levels at varying road conditions, future studies may consider both time and perception as cost functions when determining optimum routes for the accessible network layer. However, incorporating multiple cost functions introduces model complexities, as alternate routes between locations may have trade-offs between time efficiency and perceptual feasibility. To address this, future research may need to estimate additional parameters, such as the weights for each cost function, to derive a combined cost parameter. Future research may extend the survey questionnaire to help generate necessary data. Beyond rating each travel environment, participants can provide overall ratings for time and perception indicators based on how they prioritize and evaluate these factors in their daily travel decisions.

Lastly, the current modeling approach only validates the ensemble model performances in predicting soft constraints and lacks any triangulation for inclusive accessibility measures. Future studies may conduct another primary data collection, perhaps semi-structured interviews or focus group discussion-based data collection, to evaluate the accuracy of inclusive accessibility measures and means to improve it.

Despite the limitations, this study contributes to developing a method that effectively measures both spatial and social differences in travel perceptions and accessibility. By predicting the group-specific walking perception scores using ML-based algorithms, our method signifies that travelers of different socioeconomic identities have different perceptions of mobility barriers within similar travel environments. Continuing this analysis, future research can further characterize community-specific walkable travel environments by identifying the infrastructural and environmental factors influencing their perceptual variations.

7. Conclusions

The paper demonstrates a method to operationalize the bottom-up inclusive accessibility concept, using a unique mobility survey dataset from Columbus, OH, and focusing on public transit and walking. Advancing prior research, the group-specific inclusive access integrates travel perceptions predicted for socio-economic communities by systematically aggregating and modeling their individual-level data. By accounting for spatial and social variabilities in travel perceptions, inclusive access offers a more conservative, reliable, and socially sensitive approach than traditional measures.

Inclusive access, due to its ability to capture income, gender, and racial disparities in travel and access, may serve as an effective tool for equity-oriented planning and need-specific transportation investments. The data collection approach and method are replicable for any city in the United States. Besides, the method itself can be replicable without going through the rigorous data collection procedure and using alternate data sources, such as travel survey data. This method can help urban planners identify where people currently experience difficulties in terms of using alternate travel modes and how we can improve network accounting for the social differences in travel behavior and perceptions.

Author contributions: CRediT

AK: Conceptualization, Data curation, Formal analysis, Methodology, Investigation, Visualization, Writing – original draft, Writing – review & editing. NX: Methodology, Supervision, Writing – review & editing. HJM: Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing. HTKL: Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing.

CRediT authorship contribution statement

Armita Kar: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Ningchuan Xiao:** Methodology, Writing – review & editing, Supervision. **Harvey J. Miller:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing. **Huyen T.K. Le:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing.

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Appendix A

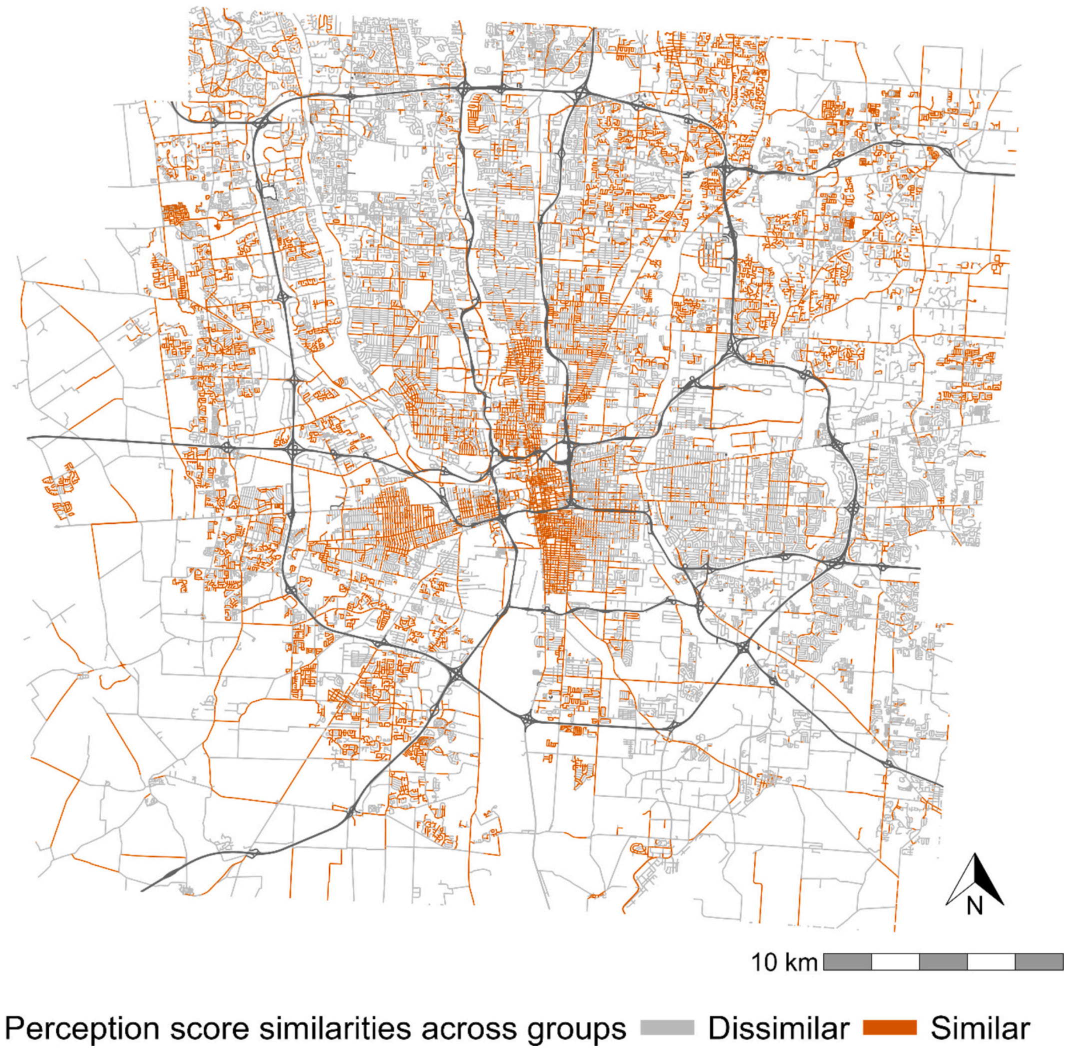

Fig. A1. The similarities in walking perception scores across four example groups: high-income white men, moderate-income women of color, low-income men of color, and low-income women of color. Each street marked in grey has different walking perception scores for at least two of these social groups, while the streets marked in orange have the same walking perception across all communities.

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