Health & Place 90 (2024) 103375

Contents lists available at ScienceDirect

Health and Place

journal homepage: www.elsevier.com/locate/healthplace

Using smartphone user mobility to unveil actual travel time to healthcare: An example of mental health facilities

Lixiaona Yu[a], Tao Hu[a,*], Taiping Liu[b], Yunyu Xiao[c,d]

[a] Department of Geography, Oklahoma State University, USA
[b] Department of Statistics, Oklahoma State University, USA
[c] Department of Population Health Sciences, Weill Cornell Medical College, Cornell University, USA
[d] Department of Psychiatry, Weill Cornell Medical College, Cornell University, USA

ARTICLE INFO

Keywords:
Travel time
Health access
Mental health services
Smartphone user mobility
Spatial regression model

ABSTRACT

Travel time to health facilities is one of the most important factors in evaluating health disparity. Previous extensive research has primarily leveraged the driving time to the nearest health facility to gauge travel time. However, such ideal travel time (ITT) may not accurately represent real individual travel time to health services and is often underestimated. This study aims to systematically understand such gaps by comparing ITT to actual travel time (ATT) derived from smartphone-based human mobility data and further identifying how various population groups across regions are most likely to be affected. This study takes mental health as an example and compares ATT with ITT to mental health facilities. Results indicate that ITT and ATT demonstrate significant disparities between urban and rural areas. ITT is consistently underestimated across the contiguous US. We compare travel times among diverse sociodemographic groups across eight geographical regions. The findings suggest that different age groups have similar travel times to mental health facilities. However, racial groups exhibit varied travel times. Hispanics have a larger percentage of the population experiencing longer ATT than ITT. We also employed spatial and non-spatial regression models, such as Ordinary Least Squares, Spatial Lag Model, and Spatial Error Model, to quantify the correlation between travel times and socioeconomic status. The results revealed that the proportion of older adults and high school dropouts positively correlates with travel times in most regions. Areas with more non-Hispanics show positive correlations with both travel times. Overall, this study reveals pronounced discrepancies between ITT and ATT, underscoring the importance of using smartphone-derived ATT to measure health accessibility.

1. Introduction

Access to timely, high-quality, and affordable health services is essential for all individuals, regardless of their sociodemographic or economic status (WHO, 2022). A lack of access can result in poor health outcomes (Alegana et al., 2018; Zipfel et al., 2021) and healthcare disparities (Rader et al., 2022; Yuan et al., 2023). Health access is evaluated in five dimensions, also known as the 5 A's: affordability, accommodation, acceptance, availability, and accessibility (Penchansky and Thomas, 1981). This framework is critical for assessing the effectiveness of health policy and service delivery, highlighting disparities in healthcare access, and guiding policy and resource allocation to improve health outcomes.

Accessibility refers to the physical access to healthcare services, considering the geographical distribution of healthcare facilities, patients' residential locations, and their transportation resources (Chen and Wang, 2022). Travel time, reflecting the inequality of access to and efficiency in the usage of health facilities, is one of the most important factors in evaluating geographical accessibility (Hiscock et al., 2008; Onitilo et al., 2014). Previous research has focused on utilizing travel time to the nearest health facility as a proximity metric to assess the accessibility of health services (Blanford et al., 2012; Huerta Munoz and Källestål, 2012). For instance, Ghorbanzadeh et al. (2020) analyzed accessibility metrics by calculating travel times from the centroids of census population block groups to the closest mental health facilities to assess spatial accessibility in Florida. Similarly, Khazanchi et al. (2022) computed drive times from the center of each census tract to the ten nearest COVID-19 Test-to-Treat sites, subsequently identifying the

* Corresponding author.
E-mail address: tao.hu@okstate.edu (T. Hu).

https://doi.org/10.1016/j.healthplace.2024.103375
Received 31 May 2024; Received in revised form 16 October 2024; Accepted 23 October 2024
Available online 29 October 2024

shortest time to assess accessibility for various subpopulations defined by race, ethnicity, age, and rurality. More recently, Rauch et al. (2023) estimated the accessibility between residences and the nearest facilities by individual driving time and public transport, uncovering spatial inequalities for elderly women in access to preventive breast cancer care services in Bavaria. The metric of travel time to the nearest health facilities has also been applied to access to SARS-CoV-2 testing sites (Rader et al., 2020) and Emergency Medical Services (EMS), such as stroke centers (Rauch et al., 2021). However, this proximity metric has significant limitations, as it assumes people only access the nearest healthcare facilities, without accounting for factors like traffic and weather conditions, language barriers, or economic challenges. Consequently, relying exclusively on proximity to gauge accessibility can lead to biased and inequitable evaluations, particularly in healthcare service selection.

Several studies have explored approaches to improve the accuracy of travel time measurement and compared these with proximity-based metrics. For instance, Zhu and Levinson (2015) used GPS (Global Positioning System) devices to accurately monitor travelers' trajectories for three weeks and found that approximately two-thirds of participants did not use the shortest travel time path. Similarly, Tang and Levinson (2018) found that most commuters prefer longer routes than the shortest available path. Alford-Teaster et al. (2016) employed survey data from Breast Cancer Surveillance Consortium and geocoded participants street level addresses to calculate actual travel time to mammography facilities. The results revealed that only 35% of women in the study population visited their closest facility. Remarkably, approximately 75% of the women chose a facility within a 5-min travel time, but not necessarily the nearest one. Researchers have identified various factors influencing route decisions, including estimated traffic time (Abdel-Aty et al., 1997), travel cost, distances, traffic conditions, drivers' habits (Chen et al., 2001), and the reliability of travel time (Train and Wilson, 2008). Beyond GPS and survey-based methods, this study aims to employ a novel data source-smartphone user mobility data-to measure actual travel time to health services with greater accuracy, offering a more comprehensive and realistic understanding of healthcare accessibility.

In recent years, especially since the COVID-19 pandemic, the utilization of smartphone user mobility data has become increasingly prevalent. This trend is underscored by the comprehensive coverage of mobility data offered by SafeGraph, capturing approximately 10% of all GPS-enabled mobile devices in the US, thus providing a well-represented cross-section of various sociodemographic groups (Hu et al., 2021; Xu et al., 2023; Zhang et al., 2022). The growing reliance on mobile data is crucial in enhancing our understanding and analyzing health access behavior. For example, Jing et al. (2023) used mobile phone-based visitation data to estimate average mental health utilization, revealing disparities among immigrant concentrations across the US. Similarly, Wei et al. (2023) tracked social distancing behavior to discover disparities in COVID-19 transmission across communities with different sociodemographic and economic statuses. Owuor and Hochmair (2023) leveraged smartphone user visitation data to discover patterns of visitation counts to several POI categories during the pandemic in Florida and California. Li et al. (2023) revealed distinct geographic disparities in visitation interruptions at Ryan White HIV facilities in the Deep South during the COVID-19 pandemic using mobile device-based visitation. Zeng et al. (2022) focused on revealing the geospatial disparities in population mobility and aging in local areas in relation to COVID-19 transmission in the Deep South. Beyond the visitation pattern, smartphone data have been instrumental in calculating travel times, a critical metric for assessing health facility access (Nilforoshan et al., 2023).

Mental health services are essential components of health care, connected to overall well-being (Bennett et al., 2015; Sartorius, 2007), and directly bearing on the quality of life (Whiteford et al., 2013). The demand for mental health services has been growing and drawing increasing attention from scholars (Yang and Wang, 2023). According to the National Alliance on Mental Illness (NAMI), in 2021, 1 in 5 adults in the US experienced mental illness each year (NAMI, 2023). However, in 2020, 48% of U.S. adults in nonmetropolitan areas with a mental illness received treatment, while 62% of those with a serious mental illness sought treatment (NAMI, 2023). This underscores the critical need for accessible mental health facilities. Scholarly concern is growing over the unequal access to these facilities (Smith-East and Neff, 2020). For example, Cummings et al. (2017) found that the lowest-income communities have a lower rate of office-based practices of mental health specialists, including physicians and nonphysicians, but a higher rate of outpatient mental health treatment facilities. Ghorbanzadeh et al. (2020) assessed accessibility in Florida by calculating weighted scores based on travel time to mental health facilities, identifying significant access gaps, especially in the rural, demographically diverse northwest. To ensure mental health equality, accessibility to mental health facilities is fundamental. Moreover, accurately measuring access, especially the method used to calculate travel time, is essential in determining estimates of accessibility. Therefore, this study will utilize smartphone mobility data to measure accurate driving time to mental health facilities.

Accurately assessing travel time is pivotal for advancing health equity. Traditional methodologies frequently gauge health access disparities by measuring travel time to the nearest facilities. However, these idealized metrics often fail to consider the practical preferences that individuals exhibit when selecting health services. To bridge this gap, our research leverages extensive smartphone user mobility data to introduce a sophisticated travel metric, precisely measuring the actual travel time to health services. Focusing on mental health as a case study, our analysis compares ideal travel time (ITT) to the nearest health facility and smartphone-derived actual travel time (ATT) at the census tract and state levels across the United States (US). We further employ bivariate choropleth maps and bivariate LISA (Local Indicators of Spatial Association) to provide a detailed visualization of spatial patterns and associations. Moreover, our study delves deeper into the interplay between sociodemographic factors and travel time disparities. We comprehensively identified discrepancies between ITT and ATT by employing an integrated approach that combines both spatial and non-spatial regression analyses. More importantly, we provided guidance to policymakers for designing and implementing precise, data-driven interventions to enhance health equity.

This paper is structured into five sections. The first section provides an overview of previous studies and the objectives of our paper. The second section describes the data and methodology used to calculate travel times and perform statistical analysis. Following this, we comprehensively compare the results between ITT and ATT. The fourth section delves into the potential findings and their societal implications. Finally, the conclusion summarizes limitations and proposes directions for future research.

2. Data and methods

2.1. Data

2.1.1. Mental health facilities

SafeGraph is a company that monitors about 10% of GPS-enabled mobile devices in the US (Li et al., 2023). The location of mental health facilities is obtained from the SafeGraph POI (Points of Interest) dataset (SafeGraph, 2023), which is distinguished by its extensive collection of basic and enriched attributes for each POI. Basic attributes include the POI's name, address, geographical coordinates (latitude and longitude), category, brand identification, and NAICS (North American Industry Classification System) code. In addition, the dataset is further enriched with various additional attributes, including operational hours, website URLs, and contact phone numbers, offering deeper insights into the accessibility and availability of mental health services.

Furthermore, the dataset's geometry attributes offer precise information regarding the physical dimensions and shapes of the POIs. These attributes ensure precise geographic coordinates of the centroid of the POI, which can be used to measure geographic access from the POI to neighborhoods. In this study, we specifically focus on mental health facilities classified under two NAICS codes: 621112, representing office-based practices of mental health specialist physicians, and 621330, indicating office-based practices of non-physician mental health professionals. Using the SafeGraph POI dataset in 2023, we extracted 113,904 mental health facilities across the contiguous US. Fig. 1 shows the spatial distribution of these facilities, revealing a significant concentration in urban areas.

2.1.2. Health facilities visit pattern data

The SafeGraph POI visit pattern dataset includes the total number of visits to a POI, the duration of these visits, the distance traveled by visitors, and the origins of these visitors at the census block group level. The determination of each device's household block group is achieved by analyzing six weeks' data collected during nighttime hours, ensuring a high degree of accuracy in identifying the residential base of mobile device users (Li et al., 2024). This dataset is gathered from sources that include anonymized and aggregated location data from mobile devices. Notably, as highlighted in their 2019 report, SafeGraph's dataset demonstrates a high correlation with the actual US Census population figures, illustrating its strong representation of real-world patterns (SafeGraph, 2019). In this study, the POI visit pattern dataset is instrumental in calculating travel time to mental health facilities.

2.1.3. Sociodemographic data

Sociodemographic and economic data are associated with health outcomes (Clouston et al., 2021; Wei et al., 2023) and the inequality of accessibility to healthcare facilities (Khazanchi et al., 2022; Rauch et al., 2023). For example, factors such as age, race/ethnicity, income, employment status, education, and rural/urban status have been extensively studied as variables associated with health outcomes (Jing et al., 2023; Yang and Wang, 2023) and health inequality (Holt and Vinopal, 2023). In addition to these variables, the relationship between limited English proficiency and health outcomes and disparities has also been reviewed as an independent risk factor (Eneriz-Wiemer et al., 2014; Wilson et al., 2005). In this study, demographic factors include the percentage of the population in different age groups, the percentages of various racial groups, including White, Black, American Indian and Alaska Native (AIAN), and Asian, and the percentages of ethnic groups, including Hispanic and Non-Hispanic populations. Additionally, socioeconomic factors include median household income, unemployment rate, percentage of the population over 25 who are high school dropouts, rural-urban status, and percentage of households limited in English proficiency. These sociodemographic and economic data are from the 2015 US Census American Community Survey (ACS, 2023). Table 1 summarizes the definition and explanation of variables.

2.1.4. Region division

The rural and urban status plays a critical role in many studies regarding accessibility and travel time (Haggerty et al., 2014; Khazanchi et al., 2022; Rauch et al., 2023). The definition of rural and urban status in this study refers to the 2010 US Department of Agriculture Economic Research Service Rural-Urban Commuting Area codes (USDA, 2023), which classifies census tracts using measures of population density, urbanization, and daily commuting into 10 primary codes. These codes contain metropolitan cores (codes 1–3) as census tract equivalents of urbanized areas, micropolitan areas (codes 4–6), small towns (cores 7–9), and rural areas (code 10). In this paper, we assigned metropolitan and micropolitan areas (codes 1–6) to urban areas while others to rural areas (see Fig. 1). To further analyze the difference in the association between travel time and sociodemographic factors in subregions, we divided the contiguous US into subregions with similar economic and social conditions. The subregion division uses the Bureau of Economic Analysis Regions (BEA, 2020), where the contiguous US is divided into 8 subregions: New England, Great Lakes, Southwest, Mideast, Plains, Far West, Southeast, and Rocky Mountain, as shown in Fig. 1.

2.2. Methodology

2.2.1. Ideal travel time (ITT) to the nearest facilities

This study defines the ITT as the shortest driving time to the nearest mental health facility. Following the method proposed by Khazanchi et al. (2022), we estimate the ITT in two main steps. First, we calculate the population centroid at the census tract level from block groups:

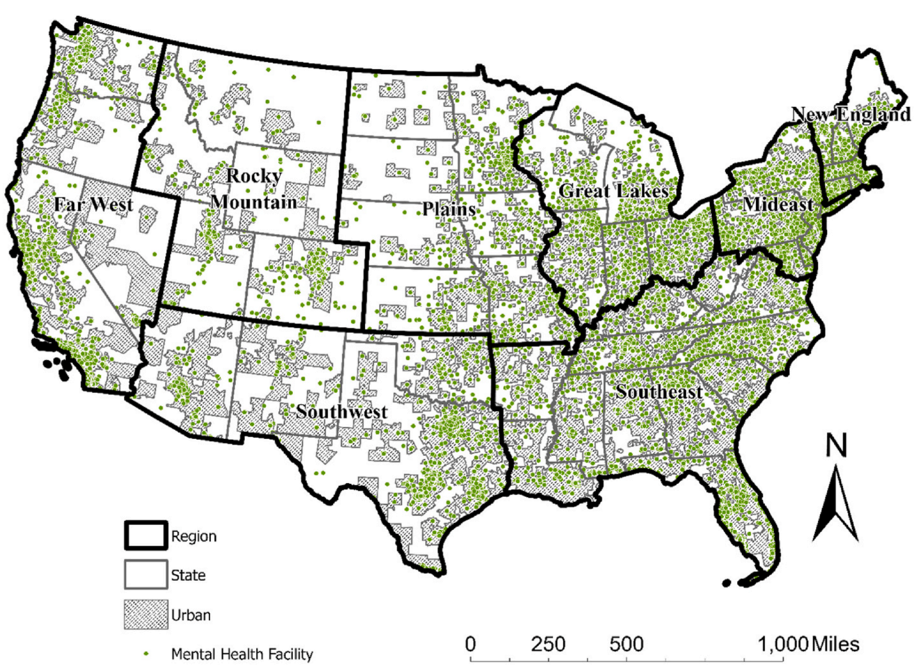

Fig. 1. Overview of study area, distribution of mental health facility, subregions, and urban areas.

Table 1
Summary of explanatory variables used in this study.

Variable	Category	Variable Name	Definition	Source
Dependent variable	Travel time	ITT	The minimum travel time from the population centroid of each census tract to the 10 nearest facilities (minutes)	Open Source Routing Machine (OSRM)
		ATT	The smartphone users' mobility data derived travel time weighted from the population centroid of each census tract to the recorded facility (minutes)	
Independent Variable	Economic	Median household income	Median household income in the past 12 months (dollars)	2015 US Census American Community Survey
	Race	White (%)	Percentage of the White population (%)	
		Black (%)	Percentage of the Black or African American population (%)	
		AIAN(%)	Percentage of the American Indian and Alaska Native alone population (%)	
		Asian (%)	Percentage of the Asian population (%)	
	Ethnicity	Hispanic (%)	Percentage of Hispanic or Latino population (%)	
		Non-Hispanic (%)	Percentage of Non-Hispanic or Non-Latino population (%)	
	Demographics	Age 65+ (%)	Percentage of the population over 65 years old (%)	
		Unemployment rate (%)	Percentage of unemployed population (%)	
		High school dropouts (%)	Percentage of population does not have high school diploma (%)	
		Households limited in English (%)	Percentage of Limited English speaking households (%)	
		isUrban	Urban/rural status	2010 US Department of Agriculture Economic Research Service

$$X_i = \sum_{j=1}^{m} X_j P_j \bigg/ \sum_{j=1}^{m} P_j,\ Y_i = \sum_{j=1}^{m} Y_j P_j \bigg/ \sum_{j=1}^{m} P_j \tag{1}$$

where X_j, Y_j is the longitude and latitude of the centroid of block group j, P_j is the population of block group j, and m is the number of block groups within census tract i.

Second, we select the top 10 nearest health facilities from the population centroid and use Open Source Routing Machine (OSRM) to calculate the driving time T_n from the population centroid to the 10 closest facilities. OSRM is a routing service based on 'OpenStreetMap' data, providing routes, isochrones, travel time and distance matrices (Huber and Rust, 2016). We get the minimum travel time among travel times from the population centroid to 10 selected facilities (Khazanchi et al., 2022) based on the equation below:

$$ITT_i = min(\mathrm{T_n}) \quad (\mathrm{n} = 1, 2, 3, \ldots, 9, 10) \tag{2}$$

2.2.2. Actual travel time (ATT) derived from smartphone user mobility data

The travel time derived from smartphone user mobility is considered ATT. As introduced in Section 2.1.2, SafeGraph data enables us to calculate the travel time from visitors' home block groups to mental health facilities. Initially, to reduce potential data noise, we removed block groups where the number of visitors to the mental health facility equals or less than 2. Then, we calculate the weighted travel time for the block group j as follows:

$$TBlock_j = \sum_{k=1}^{n} T_k V_k \bigg/ \sum_{k=1}^{n} V_k \tag{3}$$

where T_k is the travel time from block group j to mental health facility k; V_k is the number of visitors to mental health facility k; n is the number of health facilities that visitors in block group j have visited.

Based on the travel time in block groups, we further calculate the weighted travel time for the census tract as follows:

$$ATT_i = \sum_{j=1}^{m} TBlock_j V_j \bigg/ \sum_{j=1}^{m} V_j \tag{4}$$

where $TBlock_j$ is the weighted travel time for block group j; V_j is the number of visitors in block group j; m is the number of block groups within census tract i.

2.2.3. Spatial clustering analysis

Bivariate local indicator of spatial association (LISA) clustering is a multivariate spatial correlation indicator that measures local spatial autocorrelation (Anselin et al., 2002). It has been used to evaluate spatial disparity and transit equity (Jin et al., 2022; Liang et al., 2023). In this study, we use bivariate LISA to evaluate spatial disparity by examining the spatial correlation between actual and ideal driving times at the census tract level across the contiguous US. The bivariate LISA calculates the local Moran's I statistic as shown below:

$$I_i = ITT_i \sum_j W_{ij} ATT_j \tag{5}$$

where ITT_i is the ideal travel time of the census block i, ATT_j is the ATT of the census block j, and W_{ij} is the neighborhood weight matrix generated by queen contiguity weight.

Positive values for the local Moran's I indicate a positive spatial association pattern, while negative values indicate a negative association. The output Cluster Map exhibits the local spatial correlation patterns by classifying all observations into five categories: non-significant, High-High, Low-Low, Low-High, and High-Low. A 5% significance level is used to determine the statistical significance of the calculation, with groups having a p-value above this threshold considered not significant. High-High clusters indicate that areas with high values of ITT are located near high values of ATT. Conversely, Low-Low clusters indicate areas with low values of ITT are located near areas with low values of ATT. High-Low clusters identify areas with high values of ITT that are located near areas with low values of ATT, while Low-High clusters identify areas with low values of ITT that are located near areas with high values of ATT. Specifically, Low-High clusters are areas where inequity is more pronounced, as people must travel significantly farther to reach health facilities that meet their needs compared to the closest available options. The bivariate LISA is conducted using GeoDa 1.20 (Anselin et al., 2010).

2.2.4. Spatial regression analysis

To explore the contributions of representative sociodemographic and economic factors described above to travel times, we performed regression analysis for different regions and overall contiguous US at the census tract level. Traditional linear regression models, such as Ordinary Least Squares (OLS), are limited by their assumption of data linearity and do not account for potential spatial dependencies in the data. Therefore, this study utilized spatial regression models, specifically the Spatial Lag Model (SLM) and Spatial Error Model (SEM), to address spatial heterogeneity within the study area. The SLM focuses on the dependencies of variables in one area with those in surrounding areas, whereas the SEM accounts for the correlations between the error terms of an area and the errors in its neighboring areas. In this study, ITT, ATT, and the difference between ITT and ATT were analyzed using three regression models (i.e., OLS, SLM, and SEM), with the sub-datasets separated by regions.

Prior to running regression models, we checked for the multi-collinearity using the Variance Inflation Factor (VIF) and discovered no collinearity due to low VIF values (see Supplementary Table 1). Then we run the OLS regression model. Before performing the spatial regression analysis, it is essential to examine spatial correlation by calculating Global Moran's I, which ranges from −1 and 1. The value of Moran's I closer to 1 indicates a stronger spatial clustering, suggesting that similar values are more likely to be found close to each other. Conversely, a value closer to −1 indicates strong negative spatial autocorrelation, where dissimilar values are adjacent, reflecting a dispersed pattern. A value close to 0 indicates no spatial autocorrelation, meaning the values are randomly distributed across the study area with no pattern of clustering or dispersion. Global Moran's I was calculated for both ITT and ATT, with results of 0.4745 and 0.4235, respectively. These outcomes imply moderate spatial autocorrelation in the residuals, indicating that spatial regression analysis is necessary. Therefore, we conducted the SLM (Anselin, 1988) to consider the influence of neighboring values of the dependent variable on the dependent variable itself, following the equation:

$$y_i = x_i\beta + \rho\omega_i y_{j_i} + \mu_i \tag{6}$$

where y_i is the dependent variable (e.g., travel time), x_i is the independent variables (e.g., sociodemographic), β represents the regression coefficients, ρ is the spatial coefficient, ω_i is the weights matrix defining the spatial relationships between locations, $\omega_i y_j$ is the spatially lagged dependent variable for the weights matrix ω_i, and μ_i is a vector of error terms.

In addition to the SLM, we also conducted the SEM. The results of the SLM are presented in the results section, while the outcomes of linear regression and SEM are included in Supplementary Tables 2–4. We selected the SLM as the best-performing model based on its superior performance, as detailed in Supplementary Tables 5–7. Both linear and spatial regression analyses, along with the computation of Global Moran's I, were performed using GeoDa 1.20 (Anselin et al., 2010).

3. Result

3.1. Ideal travel time and actual travel time comparison

We visualized ITT and ATT through a bivariate choropleth map at the census tract level, as illustrated in Fig. 2. It is observed that ITT and ATT tend to be higher in rural areas compared to urban settings. Specifically, in urban areas, travel times exhibit greater consistency, whereas rural regions display significant variability. For instance, metropolitan areas within California demonstrate lower ATT and ITT, contrasted by surrounding rural areas marked in pink on the map, indicating significantly higher ATT relative to ITT. In the Southwest, only metropolitan areas in Texas report both travel times within 30 min, with other areas also experiencing higher ATT than ITT. The Plains region is predominantly rural, with both ATT and ITT being high. Conversely, the Mideast, Southeast, and Great Lakes regions have lower travel times, with most areas reporting both ATT and ITT within 30 min. However, most of these regions still show pink, suggesting that ATT is much higher than ITT.

Moreover, beyond the absolute value of two travel times, the difference between ATT and ITT in urban areas shows more homogeneity

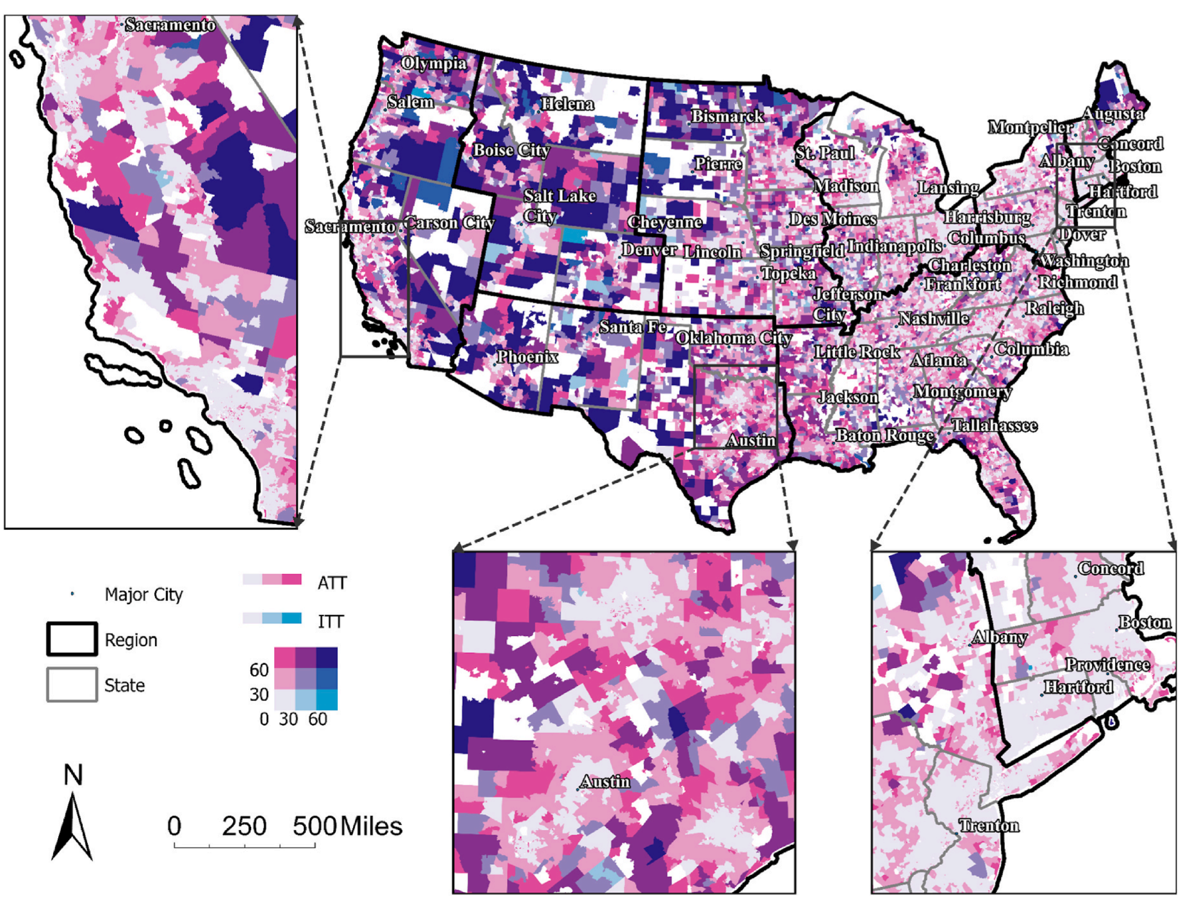

Fig. 2. Bivariate choropleth map of ATT and ITT at census tracts level.

than in rural areas. In urban settings, the difference is mostly within 15 min, meaning that urban residents' ATT is only 15 min larger than their ITT. However, for rural areas, the scenario is much more complex. Not only are rural tracts typically far from mental facilities, making the ITT quite large, but also people living in these areas need to travel more than an hour to access mental health services that meet their needs, rather than the nearest facility. In contrast, most urban residents need only a maximum of 15 min more to access their preferred mental health facilities. This shows a significant travel time gap between rural and urban residents. However, there are a few rural areas with blue/cold color, suggesting that in these areas, ATT is smaller than ITT. This analysis highlights the disparity in travel times between urban and rural areas, emphasizing the challenges faced by rural populations in accessing mental health facilities efficiently.

Fig. 3 illustrates the results of the bivariate LISA analysis, which investigates the spatial correlation between ITT and ATT. The High-High (pink) clusters, predominantly found in rural areas, signify areas of high ITT surrounded by areas of high ATT. Conversely, the Low-Low (blue) clusters are primarily situated in urban regions of major cities, including Dallas, Houston, Austin, and San Antonio in Texas; Los Angeles, San Diego, San Jose, and San Francisco in California; and Boston, Hartford, New York City, and Philadelphia on the East Coast. This indicates that residents near urban centers generally experience low ITT, surrounded by low ATT. The Low-High (light blue) clusters represent census tracts with low ITT surrounded by neighbors with high ATT. Besides the High-High and Low-Low clusters, the result reveals a great number of Low-High tracts but fewer High-Low (light pink) tracts. This suggests that using ITT as the sole measure of accessibility may underestimate the number of tracts with high ATT, especially in rural areas. Suburban communities, on the other hand, exhibit Not Significant (grey) patterns, indicating that actual driving times are distributed independently of the ideal driving times.

Furthermore, the correlation between ATT and ITT at the state level is also explored to reveal discrepancies among states, as illustrated in Fig. 4. We created scatter plots of ITT versus ATT for each census tract, with each dot representing a tract, and performed linear regression analysis between ITT and ATT for each state using the geographic topology of the corresponding state location with the R package "geofacet". The analysis shows that in almost all states, ATT is larger than ITT, which means that using ITT to estimate the travel time to mental health facilities generally results in underestimation across the contiguous US. Vermont is an exception where two travel times are the closest, with the regression coefficient of 0.97, likely due to its low population and small area. As of the 2022 US Census, Vermont is the second-least populated state and has the second-highest percentage of White residents (92.6%) (US Census Bureau, 2023). Texas (2.08) has the most significant underestimation of travel time using ITT, followed by Florida (1.85) and Michigan (1.86). Texas is also the second-largest and second-most populated state (US Census Bureau, 2023). Other states with large discrepancies between ITT and ATT include Louisiana (1.78), Massachusetts (1.77), and Washington, D.C. (1.73). Interestingly, Wyoming, despite being the least populated state, also faces a substantial underestimation of travel time to mental health facilities when measured by ITT, with a regression coefficient of 1.72.

3.2. Comparative analysis of travel times by demographic groups

We further analyzed the disparity between ITT and ATT across eight US regions, categorized by various demographic groups, including age, race, and ethnicity. Figs. 5 and 6 depict the variation in two travel time metrics among different demographic groups. The x-axis in these figures shows the percentage of the population within different travel time

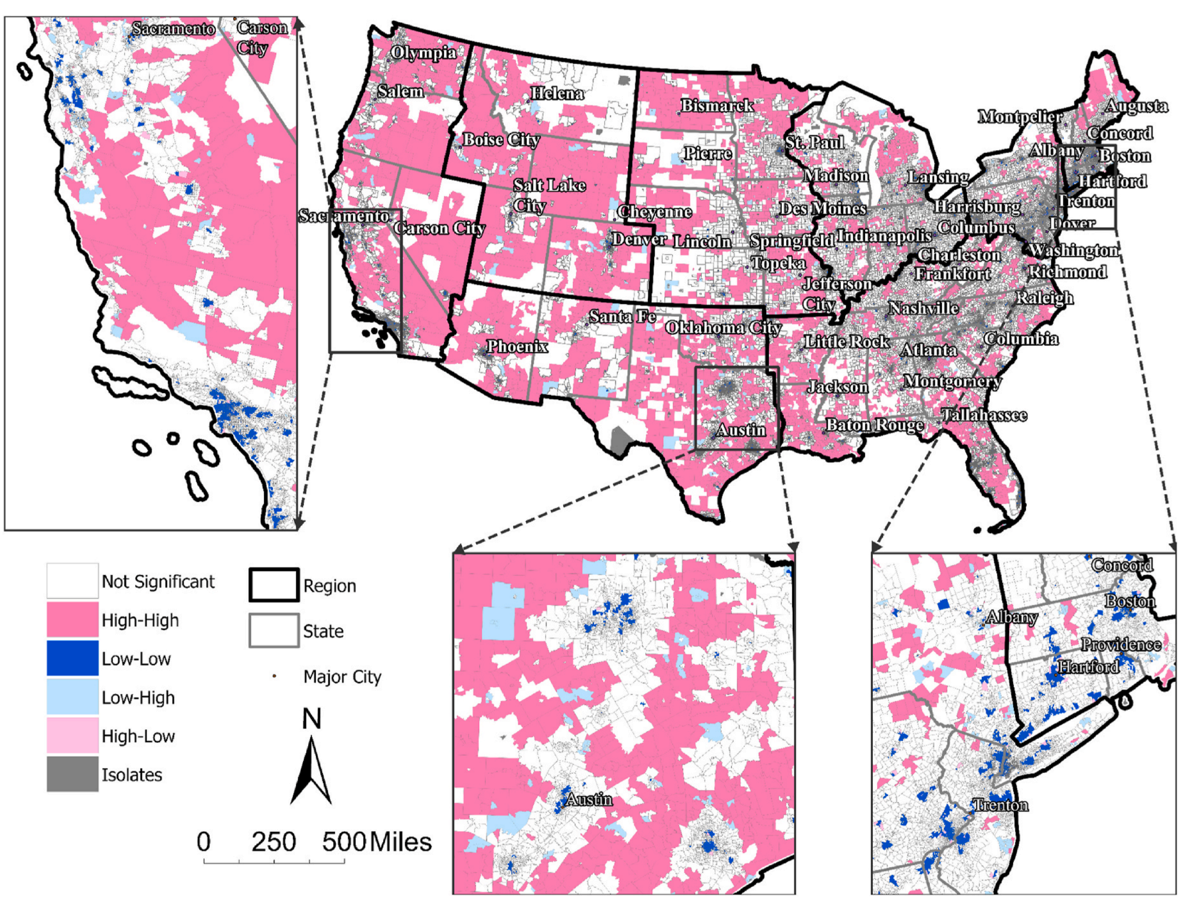

Fig. 3. Bivariate local moran cluster map.

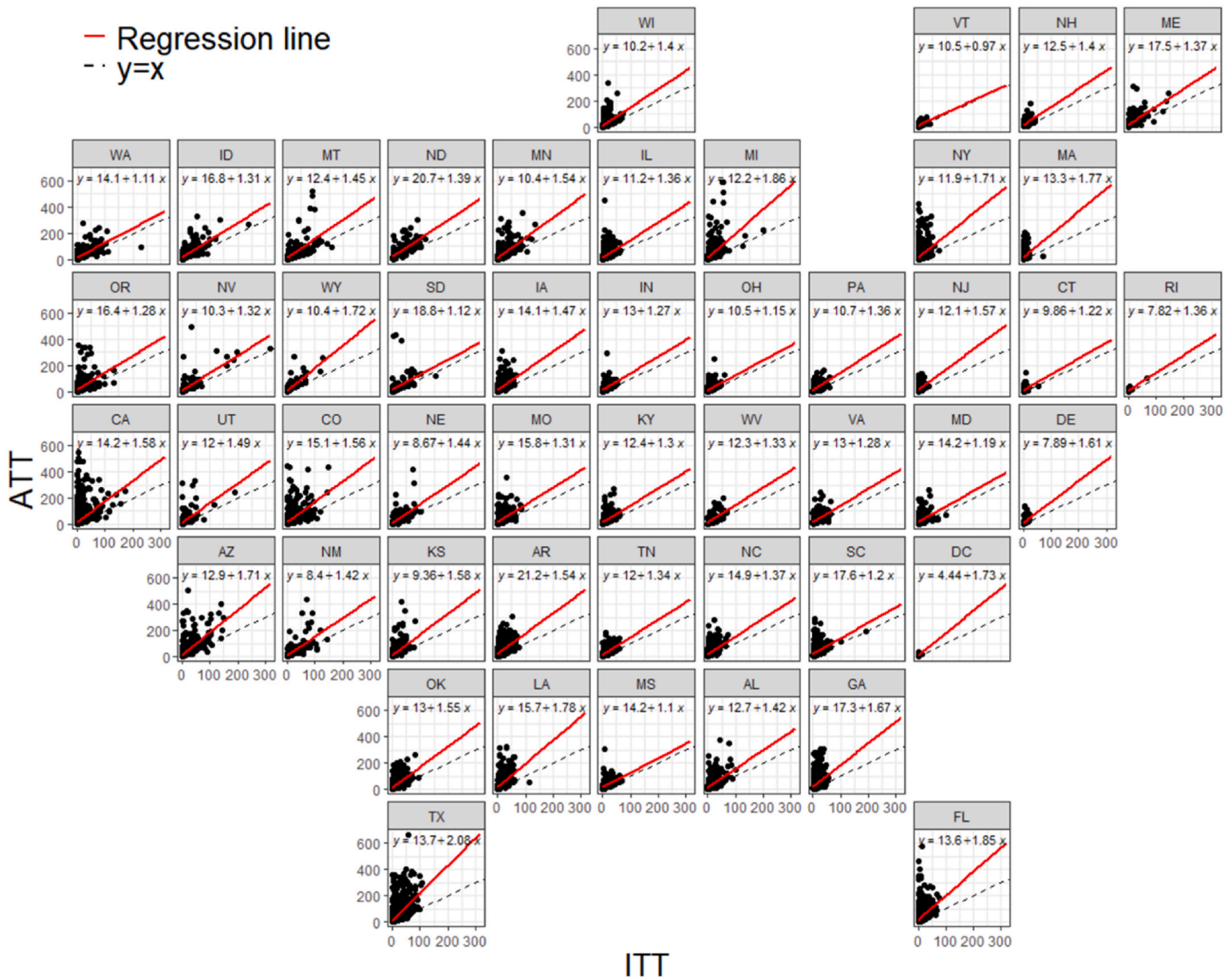

Fig. 4. Correlation between ATT and ITT at the state level.

ranges for ATT (Fig. 5) and ITT (Fig. 6). In the previous step, we assigned ATT and ITT to each census tract and obtained the percentage of population in each age group, race, and ethnicity from the sociodemographic data. This allows us to calculate the percentage of a certain demographic group within different travel time ranges for rural and urban areas separately. For example, in rural areas, the percentage of the population aged 65+ with an ATT of less than 15 min is calculated by taking the population of census tracts with an ATT of less than 15 min, multiplying it by the percentage of people aged 65+ in each census tract, and dividing it by the total population aged 65+ in rural areas.

Compared to the ITT results shown in Fig. 6, the percentage of the population with ATT within 15 min in Fig. 5 is significantly reduced, and the percentage of the population with travel time exceeding 30 min is markedly increased, especially in rural areas. In the Southwest, Rocky Mountain, Far West, Plains, and Southeast, rural residents have a higher proportion of ATT over an hour than those in New England, Mideast, and Great Lakes regions. Specifically, in rural Southwest and Rocky Mountain regions, the percentage of population with ATT between 15 and 30 (8.8% and 7.5% respectively) is much lower than other regions (e.g., 26.8% in New England), indicating that more than half of the population in these areas has ATT exceeding 30 min. Similarly, the percentage of the population in the Southwest with ATT greater than 60 min is almost double that of the Great Lakes and Mideast regions. This disparity can be attributed to several factors. The Southwest region is characterized by its vast, sparsely populated rural areas, which often have fewer healthcare facilities spread over larger distances. This results in longer travel times for residents seeking mental health services. In contrast, the Great Lakes and Mideast regions have higher population densities and better-developed infrastructure, facilitating easier access to healthcare facilities and shorter travel times. Furthermore, the concentration of healthcare facilities in urban centers within the Great Lakes and Mideast regions reduces the travel burden for rural residents in those areas.

It is further observed that ATT does not significantly differ among age groups, as shown in Fig. 5. However, significant differences in travel times by ethnicity exist in urban areas. Hispanics have a higher percentage of the population with ATT within 15 min, particularly in urban areas of New England, the Mideast, and the Plains. In contrast, across the entire contiguous United States and in the Southwest's rural areas, Hispanics have a higher percentage of population with ATT exceeding an hour compared to non-Hispanics. Regarding race, Black residents generally have a lower percentage of the population with ATT exceeding an hour in rural areas, indicating better ATT for Black residents compared to Asian and White residents, except in the Mideast. This trend is notably observed in rural areas of New England, the Southwest, the Rocky Mountain, and the Far West. In urban areas, White residents have the lowest percentage ATT less than 15 min in New England, the

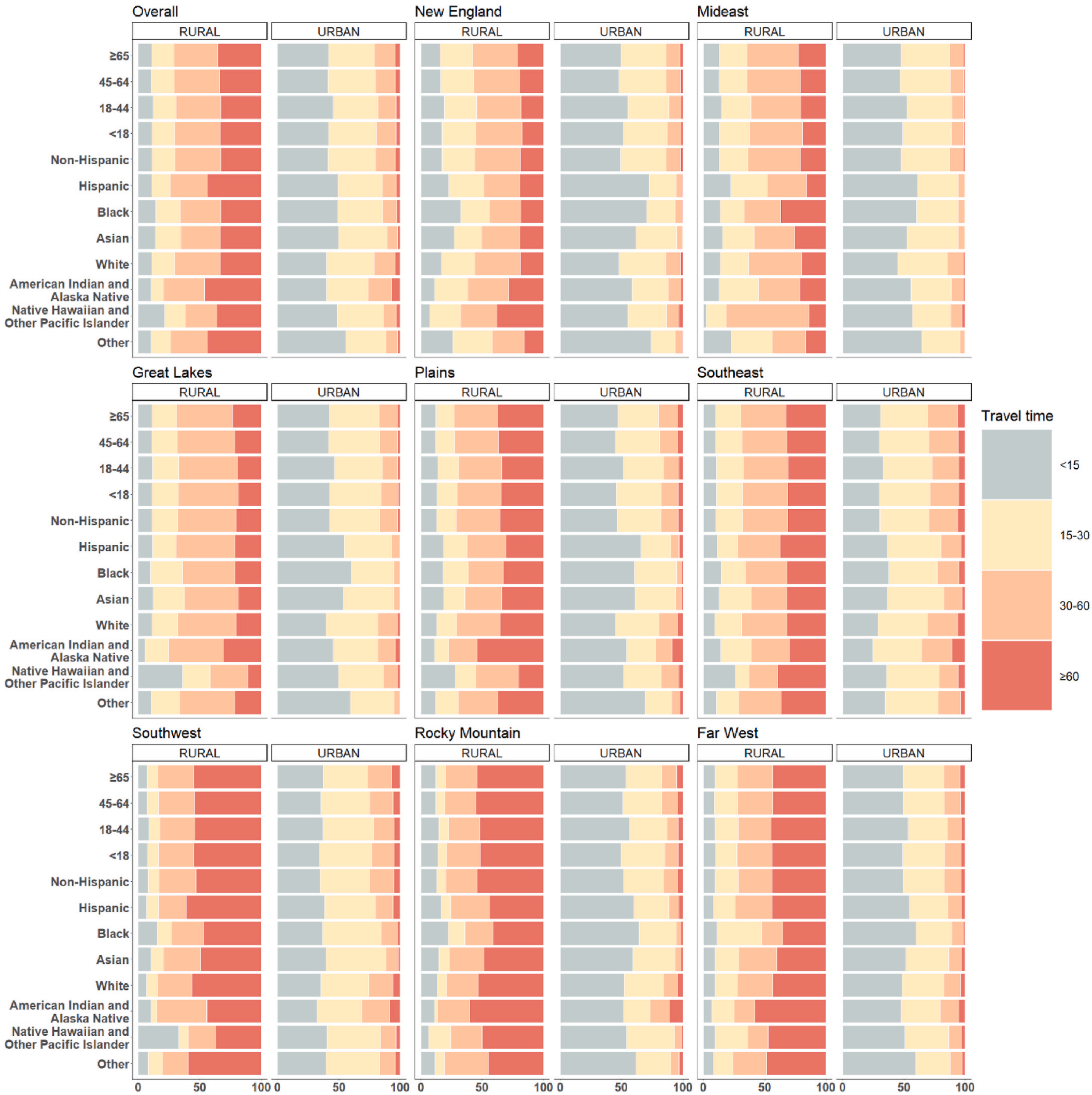

Fig. 5. Demographic difference in ATT for each sociodemographic subgroup.

Mideast, the Great Lakes, and the Plains. Additionally, Native Hawaiian and Other Pacific Islander residents have the highest percentage of ATT between 30 and 60 min. American Indian and Alaska Native residents generally have the worst travel time, with the highest proportion of ATT exceeding an hour in urban areas across all regions except New England and the Mideast.

The variation in ITT (see Fig. 6) across regions shows patterns that are both similar to and different from those of ATT. Similar to ATT, rural residents generally have longer ITT than their urban counterparts, regardless of region, race, ethnicity, or age group. Compared to New England, the Mideast, the Great Lakes, the Southeast, the Plains, the Southwest, the Rocky Mountain, and the Far West regions exhibit a higher percentage of population with ITT exceeding 1 h in rural areas. In urban areas, the majority of residents can reach the nearest mental health facilities within 15 min. Conversely, in rural regions, ITT is not only longer but also varies significantly based on race and ethnicity, with less than 50% of the population able to access the nearest mental health services within 15 min. Moreover, a portion of the rural population requires more than an hour to reach these services. Specifically, as shown in Fig. 6, in the Rocky Mountain region, more than 10% of the rural population needs to travel more than 60 min to access mental health facilities. In rural areas of New England, the Mideast, the Great Lakes, and the Southeast, a small portion of residents face travel times exceeding an hour.

Regarding age groups, similar to ATT, the results indicate minimal variation in ITT across different age groups, suggesting that age is not a

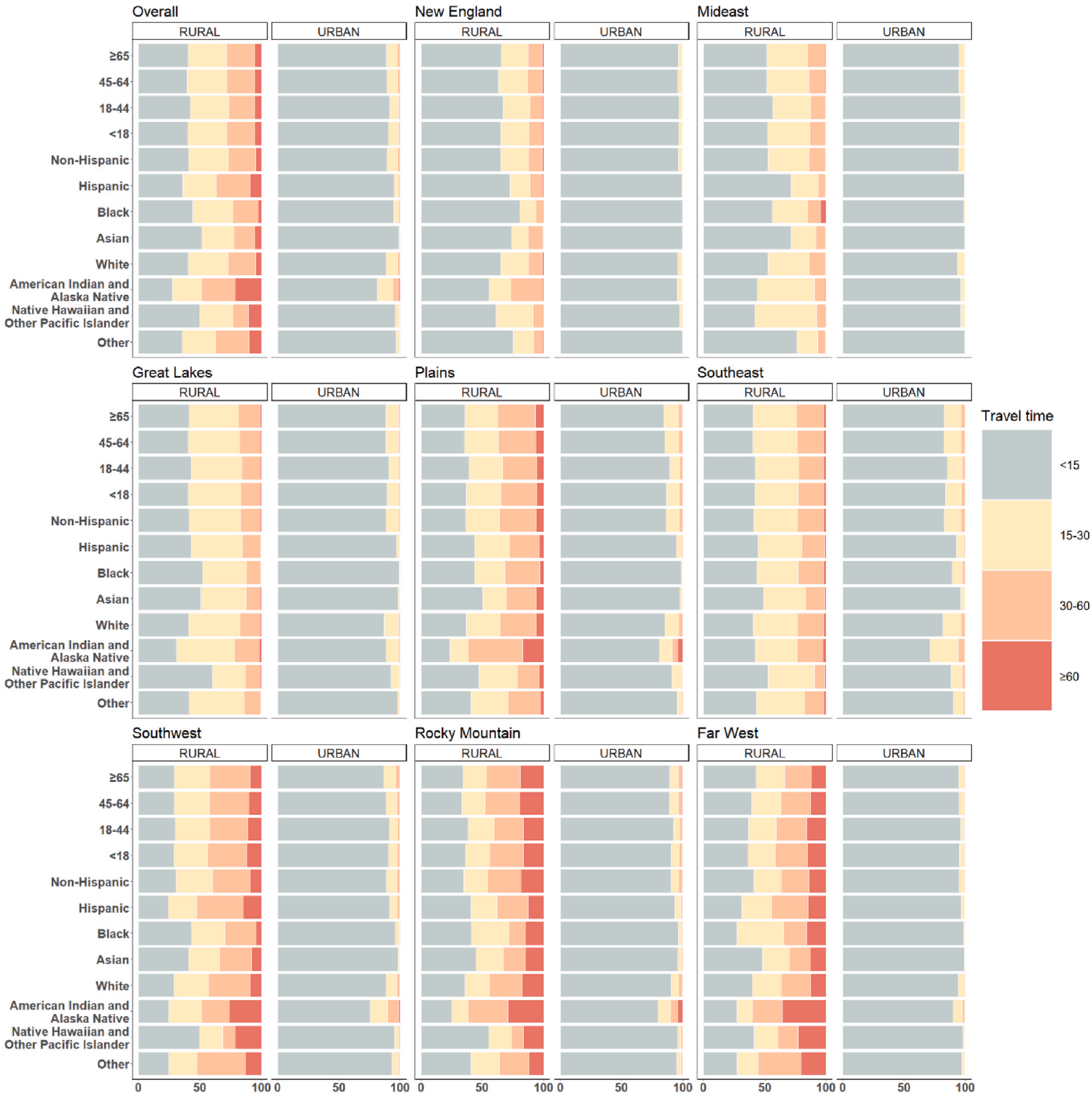

Fig. 6. Demographic difference in ITT for each sociodemographic subgroup.

predominant factor contributing to the travel time disparity. However, some patterns are notable. For example, in most regions, the 18–44 age group in rural areas has the largest percentage of the population with ITT less than 15 min, except in the Far West, where ITT tends to increase with age, especially in rural areas. In terms of ethnicity, Hispanic individuals generally experience less ITT than non-Hispanic individuals in both urban and rural areas, except for the rural Southwest and Far West regions. Among races, American Indian and Alaska Native residents generally have the longest ITT in both rural and urban areas, while Asian residents have the shortest ITT in both settings. The disparity in ITT between races is minimal in urban areas but significant in rural areas, highlighting the gap between rural and urban travel times. For example, in rural New England, Great Lakes, and Southwest, Black residents have shorter ITT than Asian and White residents. Conversely, in the rural Far West, Rocky Mountain, Southeast, Plains, and Midwest regions, Asian residents have shorter ITT than Black and White residents. Additionally, some American Indian and Alaska Native residents in urban areas of the Plains and Rocky Mountain regions have long travel times to mental health services, exceeding an hour.

3.3. *Regression results*

This section examines the association between three travel time metrics (ATT, ITT, and their differences), and sociodemographic and economic variables across the contiguous United States and its eight regions. This analysis utilizes three regression models as described in the methodology section. The corresponding results are presented in Tables 2–4.

From the regression results, it is found that rural-urban status is the most negatively significant factor in all three regression models, indicating that both travel times and the difference between them are significantly increased by the rural status. Median household income is not associated with either travel time or the difference. The percentage of older adults is positively associated with travel time in all three models. The percentage of high school dropouts is positively associated with ATT and ITT, but negatively associated with the difference, meaning that high education would mitigate the increase in ATT more significantly than ITT.

Table 2 provides the SLM modeling results of ATT across various regions, highlighting the impact of several demographic and socioeconomic factors. The percentage of the population aged 65 and older demonstrates a highly significant positive association ($p < 0.001$) with ATT in the contiguous US, Great Lakes, Plains, and Far West. The unemployment rate exhibits a statistically significant positive association with ATT in the Great Lakes and Far West, while showing a significant negative association in the Plains. Additionally, the percentage of high school dropouts highly significantly increases ($p < 0.001$) ATT in the contiguous US, Plains, and Southeast. This indicates that higher dropout rates are associated with longer travel times to access mental health services in these regions. Regarding races, the percentage of Black residents has a significant negative association with ATT in the contiguous US, the Great Lakes, Southeast, Southwest, and Far West. Similarly, a higher percentage of Asian residents is negatively associated with ATT in the contiguous US, New England, Great Lakes, Southeast, Southwest, and Rocky Mountain. In contrast, an increase in AIAN populations ($p < 0.001$) highly significantly raises ATT in the contiguous US, Great Lakes, Plains, Rocky Mountain, and Far West. Furthermore, the percentage of households with limited English proficiency has a highly significant negative association ($p < 0.001$) with ATT in the contiguous US, and significant negative in the Mideast and Far West but positive in Southwest. Urban status has a highly significant negative association ($p < 0.001$) with ATT in all regions, indicating that urban areas generally have shorter travel times to mental health services compared to rural areas. This effect is particularly pronounced in the Rocky Mountain region, where the coefficient reaches as low as −39.07.

Table 3 presents the SLM modeling results of ITT across various regions. It is shown that higher median household income is highly significant with the ITT ($p < 0.001$) in the contiguous US, Great Lakes, Plains, Southeast, and Far West, suggesting economic well-being may influence health service access. The percentage of the population 65+ is positively associated with ITT with high significance ($p < 0.001$) in the contiguous US, Great Lakes, Plains, and Rocky Mountain. The percentage of high school dropouts could increase the ITT significantly in most regions, except in New England. This indicates that lower educational attainment may correlate with reduced access to mental health facilities. Additionally, the negative association for the unemployment rate, observed only in the contiguous US and the Rocky Mountain region, suggests that higher unemployment rates are linked with shorter travel times to mental health facilities in these areas. Regarding race and ethnicity, the results are similar to those observed for ATT. The higher percentage of AIAN is directly linked to longer ITT. Conversely, the percentage of Black and Asian residents shows a negative association with ITT. Additionally, Hispanic population is significant negatively associated with the ITT in most regions, except for New England, suggesting that non-Hispanic population tends to have longer ITT. The results for households limited in English proficiency show a significant negative association with ITT in the contiguous US, Mideast, and Southeast only. Similar to the ATT results, rural status highly significantly increases ($p < 0.001$) ITT in all regions, though the effect is not as substantial as in the ATT results. This effect is particularly pronounced in the Rocky Mountain and Far West regions, where the coefficients exceed 10.

Table 4 provides the SLM modeling results for the difference between ATT and ITT across various regions. The impact of median household income is marginally significant in the contiguous US, Mideast, and Southeast. The percentage of the population aged 65 and over has a highly significant positive association ($p < 0.001$) in the contiguous US, New England, Great Lakes, Southeast, and Far West, indicating the aging population has a larger bias if ITT is used as an estimator of their travel time to mental health facilities. The unemployment rate shows varied results, with a notably significant positive association in the Great Lakes region and a significant negative association in the Plains region. High school dropout rates have a significant negative association in the contiguous U.S., Mideast, Great Lakes, Southeast, and Southwest regions, while the Plains region shows a significant positive association. Regarding races, the percentage of Black has a highly significant negative association ($p < 0.001$) with ATT-ITT in the contiguous US, Mideast, Great Lakes, Southeast, indicating the travel time of Black population is overestimated by ITT in those regions. The AIAN population shows a highly significant positive association ($p < 0.001$) in the contiguous U. S., Great Lakes, and Plains regions, suggesting that AIAN residents are likely to experience greater underestimation of travel time when measured by ITT. As for ethnicity, the percentage of Hispanic population shows a highly significant positive association ($p < 0.001$) in the contiguous US, with varied regional impacts. This includes a negative association in New England and Plains, but a positive association in the Far West. Moreover, limited English proficiency shows a significant negative association in the contiguous US and Far West, but a positive association in Southwest. The urbanity variable consistently shows a highly significant reduction ($p < 0.001$) in the difference across all

Table 2
The result of the SLM for ATT.

	Overall	New England	Mideast	Great Lakes	Plains	Southeast	Southwest	Rocky Mountain	Far West
Median household income	0.00	0.00	0.00[c]	0.00	0.00[b]	0.00	0.00	0.00	0.00[b]
Age 65+ (%)	0.14[d]	0.23[c]	0.04	0.20[d]	0.36[d]	0.06[c]	0.07[a]	0.13	0.18[d]
Unemployment rate (%)	−0.02	0.07	0.05	0.08[b]	−0.36[c]	0.02	−0.01	−0.36	0.13[b]
High school dropouts (%)	0.05[d]	0.01	−0.04	−0.02	0.47[d]	0.11[d]	−0.06	−0.05	0.01
Black (%)	−0.04[d]	−0.04	−0.04[d]	−0.06[d]	−0.05	−0.07[d]	−0.08[d]	0.00	−0.09[c]
AIAN (%)	0.31[d]	1.08[c]	0.08	0.54[d]	0.54[d]	0.05	0.13[c]	0.54[d]	0.56[d]
Asian (%)	−0.05[d]	−0.16[c]	−0.01	−0.12[c]	−0.20[a]	−0.18[d]	−0.20[c]	−0.69[b]	0.01
Hispanic (%)	−0.01[a]	−0.11[c]	−0.02[a]	−0.04[b]	−0.30[d]	−0.07[d]	−0.00	−0.11	0.01
Limited in English (%)	−0.09[d]	0.05	−0.07[b]	0.00	−0.11	−0.05	0.12[b]	0.35	−0.12[b]
isUrban	−16.01[d]	−11.55[d]	−18.27[d]	−9.76[d]	−15.56[d]	−9.59[d]	−25.81[d]	−39.07[d]	−31.24[d]

Note.
All values are rounded to two decimal places. A value of 0.00 represents a coefficient that is very small but non-zero.
[a] $p < 0.1$.
[b] $p < 0.05$.
[c] $p < 0.01$.
[d] $p < 0.001$.

Table 3
The result of the SLM for ITT.

	Overall	New England	Mideast	Great Lakes	Plains	Southeast	Southwest	Rocky Mountain	Far West
Median household income	0.00[d]	0.00[b]	0.00[c]	0.00[d]	0.00[d]	0.00[d]	0.00[b]	0.00[a]	0.00[d]
Age 65+ (%)	0.03[d]	0.01	0.01	0.04[d]	0.12[d]	0.01	0.02[b]	0.18[d]	−0.01
Unemployment rate (%)	−0.02[d]	0.00	−0.01	0.01	−0.02	−0.01	−0.03	−0.21[b]	0.03
High school dropouts (%)	0.09[d]	0.02	0.05[d]	0.05[d]	0.15[d]	0.14[d]	0.06[d]	0.18[b]	0.05[d]
Black (%)	−0.02[d]	−0.01	−0.01[d]	−0.02[d]	−0.01	−0.03[d]	−0.03[d]	0.03	−0.02[b]
AIAN (%)	0.15[d]	0.45[c]	0.07[b]	0.11[d]	0.12[d]	0.05[c]	0.09[d]	0.40[d]	0.42[d]
Asian (%)	−0.04[d]	−0.05[c]	−0.02[d]	−0.07[d]	−0.09[c]	−0.09[d]	−0.06[d]	−0.20[a]	−0.02[c]
Hispanic (%)	−0.03[d]	−0.02	−0.03[d]	−0.04[d]	−0.11[d]	−0.04[d]	−0.02[d]	−0.11[c]	−0.03[d]
Limited in English (%)	−0.04[d]	−0.03	−0.03[d]	−0.00	0.04	−0.04[c]	−0.01	0.02	−0.02
isUrban	−4.04[d]	−3.26[d]	−2.00[d]	−2.61[d]	−4.06[d]	−1.13[d]	−6.17[d]	−15.30[d]	−10.65[d]

Note.
All values are rounded to two decimal places. A value of 0.00 represents a coefficient that is very small but non-zero.
[a] $p < 0.1$.
[b] $p < 0.05$.
[c] $p < 0.01$.
[d] $p < 0.001$.

Table 4
The result of the SLM for ATT-ITT.

	Overall	New England	Mideast	Great Lakes	Plains	Southeast	Southwest	Rocky Mountain	Far West
Median household income	0.00[b]	0.00	0.00[b]	0.00[a]	0.00	0.00[b]	0.00	0.00	0.00
Age 65+ (%)	0.12[d]	0.24[d]	0.04	0.16[d]	0.21[c]	0.06[d]	0.03	−0.04	0.20[d]
Unemployment rate (%)	0.01	0.08	0.06[a]	0.08[b]	−0.30[b]	0.03	0.01	−0.10	0.11[a]
High school dropouts (%)	−0.05[d]	−0.01	−0.12[d]	−0.08[c]	0.26[c]	−0.07[c]	−0.13[c]	−0.25	−0.06
Black (%)	−0.02[d]	−0.03	−0.02[d]	−0.03[d]	−0.02	−0.03[d]	−0.05[b]	−0.05	−0.07[b]
AIAN (%)	0.14[d]	0.64	0.01	0.44[d]	0.34[d]	−0.00	0.01	0.13	0.12
Asian (%)	0.00	−0.11[b]	0.02	−0.03	−0.05	−0.06	−0.13[b]	−0.55[b]	0.04[b]
Hispanic (%)	0.03[d]	−0.10[c]	0.01	0.00	−0.15[b]	−0.02	0.03	0.00	0.05[b]
Limited in English (%)	−0.05[b]	0.10	−0.03	0.02	−0.15	−0.00	0.13[b]	0.36	−0.10[b]
isUrban	−11.50[d]	−8.00[d]	−14.92[d]	−6.98[d]	−9.07[d]	−8.17[d]	−18.9[d]	−26.70[d]	−19.75[d]

Note.
All values are rounded to two decimal places. A value of 0.00 represents a coefficient that is very small but non-zero.
[a] $p < 0.1$.
[b] $p < 0.05$.
[c] $p < 0.01$.
[d] $p < 0.001$.

regions, emphasizing that the underestimation of travel time is more pronounced for rural residents compared to their urban counterparts.

4. Discussion

This is the first study to estimate the demographic disparities in travel time to mental health facilities using smartphone user mobility data. This study utilizes this data in a novel way to calculate ATT. Results demonstrate that extra time is needed when people are seeking mental health services to fulfill their needs rather than just choosing the closest facilities, especially in rural areas. Moreover, our work investigated the relations between sociodemographic factors and travel time in the contiguous US and various regions to provide insightful findings to health researchers and policy makers.

One of the key findings from the study is the notable underestimation of travel times to mental health facilities when relying solely on ITT. The difference between the ITT and the ATT exhibits the pronounced disparity faced by residents in rural versus urban areas. Rural residents consistently experience longer travel times in both ITT and ATT. As depicted in Fig. 2, most urban central areas have ITT within 30 min while a great number of rural areas require more than an hour of travel time to reach the nearest mental health facility. This distinction between rural and urban access aligns with previous research, underscoring significant accessibility barriers that are distinctly present in rural settings (Ghorbanzadeh et al., 2020; Rauch et al., 2023). Many rural Americans have less access to mental health services than their urban counterparts (Safran et al., 2009), which could potentially correspond to significant disparities in mental health outcomes for rural residents (Morales et al., 2020). In addition to the longer travel time, the larger difference between ITT and ATT is also aggregated in rural areas. According to our results, residents in rural areas face more inequality than those in urban areas if ITT is used as the measurement of accessibility. Approximately half of the urban residents would only need an extra 15 min to fulfill their needs beyond the nearest facility, and nearly 90% need less than 30 min extra. However, half of rural residents require 30 min or more.

Besides the rural and urban status, demographic disparities in access to mental health services exist as well. From the regression analysis result, it is found that age is also a significant factor. Census tracts with a higher concentration of older adults experience longer travel times and a larger difference between ITT and ATT in terms of mental health service access compared to areas with younger residents. Previous study indicates that a disproportionate share of older adults live in rural areas (Cohen and Greaney, 2023), with 17.5% of the rural population being 65 years and older compared to only 13.8% in urban areas (Smith and Trevelyan, 2019). The older adults in rural areas may face greater barriers to accessing mental health facilities. Additionally, we found that the Hispanic population is significantly negatively associated with ITT in all regions except for New England, while it is significantly associated with ATT only in New England, the Great Lakes, Plains, and Southeast regions. Although Asians represent the most urbanized ethnic group in the US, with around 95% living in urban rather than rural areas, this primarily demonstrates improved access as depicted in Fig. 6 concerning ITT, but not in the results of ATT. These findings highlight the complexity of demographic disparities in accessing mental health services and underscore the need for more accurate measures, like ATT, to understand and address these disparities effectively.

To the best of our knowledge, no other research in health services has utilized large-scale smartphone data to attain such a granular level of detail in travel time analysis within the US. This study measures ATTs to mental health services, thereby providing a more precise evaluation of patient travel times. Numerous studies have demonstrated an association between travel time to health facilities and patient health outcomes (Kelly et al., 2016; Caldwell et al., 2016)). Consequently, neglecting ATT could potentially lead to an underestimation of the impact of travel time on health outcomes. This is particularly significant in rural areas where travel distances can be considerable. Furthermore, the measurement of ATT enables researchers to accurately identify potential barriers preventing patients from accessing the nearest health facilities. These barriers could include transportation issues, previous negative experiences with the healthcare system, lengthy waitlists for appointments, and the acceptance of health insurance (Ahmed et al., 2001; Brems et al., 2006). This nuanced understanding can significantly aid decision-makers in optimizing healthcare services. It can also inform the strategic allocation of services to minimize travel time, thereby enhancing accessibility. Ultimately, the actual travel time could contribute significantly to the improvement of health outcomes by ensuring that patients can access the care they need in a timely manner. Therefore, this research has the potential to facilitate health policy decisions and shape future strategies in healthcare service provision.

Overall, this research contributes significantly to the understanding of health disparities by highlighting the inadequacy of ITT in accurately assessing accessibility to mental health services. By advocating for the use of ATT and incorporating diverse sociodemographic factors into the analysis, the study provides valuable insights for policymakers and healthcare practitioners. Research has shown that poor health access could potentially result in worse health outcomes (Kelly et al., 2016). As demonstrated in this study, the rural area's travel behavior cannot be estimated by proximity measurement, this study highlights the need for policymakers to act on tailored interventions. Many prior studies have emphasized the necessity of both horizontal and vertical equity, appealing to the distribution of accessibility benefits that should not be evenly distributed among all regions but target populations in need specifically (Ashik et al., 2024; Guo and Brakewood, 2024). Texas, Florida, Michigan, 3 states having the most underestimated travel time using ITT, also need targeted interventions to improve real accessibility, such as preferential support transit policy, tax breaks or grants, online resources, remote techniques, etc. (Cyr et al., 2019). Especially the Low-High cluster areas in Fig. 5 experiencing disproportionate disparity are where people are in greater need and demand to receive more action from policymakers and urban planners. From the regression results, the significance and direction coefficient are different in the overall US from each region, which means that the spatial heterogeneity must be included in the consideration. It is crucial to tackle these significant disparities in travel times to guarantee that everyone, irrespective of their geographical location or demographic characteristics, has fair access to healthcare. Moving forward, future research should continue to explore innovative methodologies and data sources to further elucidate the complexities of health disparities and inform targeted interventions and policies.

5. Conclusion

This study systematically compares conventional driving time metrics and smartphone-derived ATT to mental health facilities. It uncovers pronounced discrepancies, particularly within certain geographical regions and specific demographic groups. Such discrepancies underscore the importance of using ATT as a measure of health accessibility in future research. The findings of the study will contribute to the development of more equitable healthcare systems, ensuring that vulnerable populations have better access to the health services they need.

While smartphone-based SafeGraph data offers invaluable insights into human mobility patterns, critical limitations must be acknowledged to ensure the robustness of research findings. Firstly, the representativeness of SafeGraph's dataset is contingent on smartphone ownership and usage, which may not uniformly capture all demographic groups and regions, potentially biasing outcomes toward certain populations in rural areas (Curtis et al., 2022). Secondly, while SafeGraph data captures POI visit information, it does not always accurately reflect detailed visitor information. For example, visits to hospitals may include not only patients but also accompanying family members, making it difficult to discern the exact purpose of the visit. This limitation can impact analyses that require precise visitation counts and the context of those visits. Thirdly, privacy concerns and data anonymization processes can lead to the exclusion of small visitation events, thus underrepresenting less frequent or shorter visits to health facilities (Middleton et al., 2013). In contrast, conventional surveys, especially when augmented by GPS tracking, emerge as reliable and precise methods for documenting daily travel behavior, offering direct feedback in the absence of alternative data sources (Schneider et al., 2013) and also an efficient supplement to direct individual feedback when there is a lack of other data sources (Carson et al., 2023; Jiménez-Espada et al., 2022). Nonetheless, this approach is constrained by financial, temporal, and representational limitations, restricting its broader application. Hence, employing a combination of multi-source data, including smartphone mobility data, GPS tracking, and surveys, presents a comprehensive solution for accurately understanding complex travel behaviors, particularly in rural settings (Kelly et al., 2016; Cummings et al., 2017).

In addition to the SafeGraph data, the calculation of travel time in this study is based solely on driving durations, omitting other modes of transportation. This approach particularly overlooks the robust public transit systems available in certain urban centers, such as Boston and New York City, where alternatives to driving are extensively utilized and highly efficient, such as bus and subway. Therefore, it is important to consider multiple modes of transportation to assess travel time systematically and accurately. Another focus would be further exploration of the association between sociodemographic and travel time using advanced spatial regression models, e.g., Geographically Weighted Regression (GWR) and Multiscale Geographically Weighted Regression (MGWR). Beyond identifying sociodemographic correlations, it is also crucial to investigate how disparities in healthcare access impact health outcomes. Specifically, the link between limited access to mental health services and adverse mental health outcomes can be further examined. For instance, individuals who face significant barriers in accessing mental health care may experience worsening symptoms, delayed treatment, and overall poorer mental health. This could lead to increased rates of depression, anxiety, and other mental health disorders. Lastly, expanding the scope to general public healthcare, in addition to mental health services, can illuminate broader obstacles and deficiencies within the health sector.

CRediT authorship contribution statement

Lixiaona Yu: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. **Tao Hu:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Taiping Liu:** Software, Data curation. **Yunyu Xiao:** Writing – review & editing.

Funding disclosure

This project was supported by funding from the National Science Foundation (2327844), Oklahoma Rural Renewal Initiative (RRI) Seed Grant, the Artificial Intelligence/Machine Learning Consortium to Advance Health Equity and Researcher Diversity (AIM-AHEAD), a program of the National Institutes of Health (1OT2OD032581-02-259), and grants from the National Institute of Mental Health (RF1MH134649), American Foundation for Suicide Prevention (YIG-2-133-22), Mental Health Research Network, Google, Bill & Melinda Gates Foundation, National Institute for Health Care Management, National Institute on Drug Abuse Center for Health Economics of Treatment Interventions for Substance Use Disorder, HCV, and HIV (CHERISH).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2024.103375.

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