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Modeling multimodal access to primary care in an urban environment

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ABSTRACT

Access to primary health care facilities is a key component of public health, and measuring that access is vital to understanding how to target interventions. Transportation is one dimension of access and measuring distance via multiple modes allows better understanding of how varied populations access health care, particularly those who do not have access to a personal vehicle. This work builds on the 2-Step Floating Catchment Area (2SFCA) method to include travel by car, bus, bicycle, and walking. Travel time data are sourced from OpenStreetMap and transit data incorporates stop and schedule information from the General Transit Feed Specification (GTFS). Open source data analysis tools are used to aid reproducibility in other geographic contexts. Modal weights are assigned to measure the population accessing each facility by each mode. Access values for Milwaukee County in Wisconsin, USA are presented, with clear differences shown among modes accessing primary healthcare. Car access is high and consistent across the county, while biking and walking access are more impacted by distance to destination. Transit access is unequal across the county with some tracts showing no access at all. The highly varied access results by mode emphasize the importance of measuring access and travel by non-car modes, particularly when targeting communities with high rates of no car ownership. Improvement of multimodal access measurement will allow for targeted interventions that account for the availability of modes in each community.

Introduction

Primary healthcare and the transportation system

Transportation and public health are interconnected, as the transportation system can directly affect accessibility to health care services. The term 'access,' as it pertains to health care, is multi-dimensional and goes beyond the distance patients must travel to access care. Penchansky and Thomas identified five of these dimensions to access: availability, accessibility, accommodation, affordability, and acceptability, two of which, availability and accessibility, are within the spatial realm (Penchansky and Thomas, 1981). The United States Health Resources and Services Administration (HRSA) considers thirty minutes of travel time the maximum time acceptable to access primary healthcare services. This value serves as a proxy for the dimension of accessibility, while the population-to-practitioner ratio serves as a proxy for availability. These values are used to identify Health Profession Shortage Areas (HPSAs), a federal designation that allocates healthcare resources. Providing access to primary care and preventative services is a main objective of HRSA for several reasons (Health Resources and Services Administration, 2021). Utilization of primary care lessens the burden on emergency medical services to provide non-emergent care, bringing down overall cost, and gives patients a point of contact for referrals to specialists. Primary care has also been shown to improve overall patient health and lessen disparities in healthcare across population subgroups (Starfield et al., 2005).

Milwaukee County, Wisconsin borders Lake Michigan in the midwestern region of the United States (Fig. 1). It is comprised of 19 cities, including the eponymous City of Milwaukee. The city contains two areas that are classified as "high needs geographic HSPAs" due to low population-to-practitioner ratios and high rates of poverty. This means that residents in these areas may need to travel further to receive primary healthcare services. This burden is further compounded for residents who do not own personal vehicles and rely on alternative forms of transportation to access the healthcare system. This research depicts the state of primary healthcare accessibility in Milwaukee County using a Gaussian 2-Step Floating Catchment Analysis (G2SFCA) for four modes of transit: personal vehicles, walking, cycling, and public transit.

Catchment analysis for measuring access to primary healthcare

The two-step floating catchment area method (2SFCA) considers

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both the distance individuals must travel to access care and the supply of primary care physicians available to identify areas of low access. Prior research on healthcare access noted the challenges of using straight line “as the crow flies” distances and assumptions about average travel speed when geographic features and the layout of the road network prevent straight travel paths (Martin et al., 2002; Peng, 1997). The utilization of geographic information systems (GIS) in network analysis allowed for the creation of irregularly shaped catchment windows but still relied on assumptions about average travel speed (Luo and Wang, 2003). Advanced datasets of geospatial information such as those taken from Google Maps and Open Street Maps can further leverage route choice and travel times data, using speed limits on individual roads and traffic conditions (Park and Goldberg, 2021).

In terms of selecting a travel time threshold, 30-minutes has been widely used for catchment research conducted within the United States in concordance with the federal definition of an HPSA (Bosanac et al., 1976; Delamater, 2013; Luo and Wang, 2003; Mao and Nekorchuk, 2013; Yang et al., 2006). Outside of the US, travel time thresholds vary from as low as 10-minutes (Langford and Higgs, 2006) to as high as 120-minutes (Tao et al., 2018), though some international studies have elected to use the 30-minute threshold as well (Kaur Khakh et al., 2019; Schuurman et al., 2006).

This paper builds upon prior research by performing a G2SFCA using the open-source statistical analysis software R for Milwaukee County. The software was integrated with travel time data from Open Street Maps (OSM) and transit schedule and routing data from the General Transit Feed Specification (GTFS) for the Milwaukee County Transit System (MCTS). This method generates highly accurate measures of travel time for the most common transit modes (personal vehicles, walking, cycling, and public transit) and allows for comparisons of access across modal splits. All data and software used in this analysis is open source, so the methodology can be reproduced in other geographical contexts with relative ease and minimal cost.

Material and methods

Travel times

Travel time between origin and destination serves as a friction factor in the analysis of spatial access, with longer trips being less desirable and representing lower access. In studying multiple modes, it was important to incorporate detailed network information to gain the most accurate estimates. Travel times for car, biking, and walking were gathered using Open Street Map (OSM) using the Open Route Service library for R (HeiGIT, 2008; OpenStreetMap contributors, 2017). OSM offers rich information on the transportation network, including bike and pedestrian facilities. These routes consider speed limits but not real-time travel time. For bike routing, the routing algorithm prefers roads with bike facilities (e.g., bike lanes or separate trails) and minimizes elevation changes along routes. Walking routes similarly minimize elevation changes, as well as considering sidewalks and other facilities marked by users as accessible to pedestrians.

Transit data offers a different challenge, as buses operate on fixed routes and schedules. To analyze bus access, General Transit Feed Specification (GTFS) data for Milwaukee County was tied to the OSM network using the Open Trip Planner tool (Morgan et al., 2019). This uses information on stop location and schedules to plan bus trips. Travelers were assumed to walk to their stops, with an upper limit of 1 km between the stop and origin or destination. This walking distance is an artifact of using the population-weighted centroid rather than address-based data and ensures that census tracts with bus stops located along their borders are appropriately included in the analysis. Bus travel times were taken from the schedule, and transit times consisted of the sum of time spent walking, waiting, and riding the bus, as well as considering the number of transfers in a route.

For this study, appointments were assumed to happen every fifteen minutes from 8:00 AM to 4:45 PM and routes accommodated arrival five minutes before the scheduled appointment time. This allowed for information to be gathered about the variability of travel times throughout the day. As transit systems often have less headway between vehicles during peak travel times, the median for each origin–destination pair

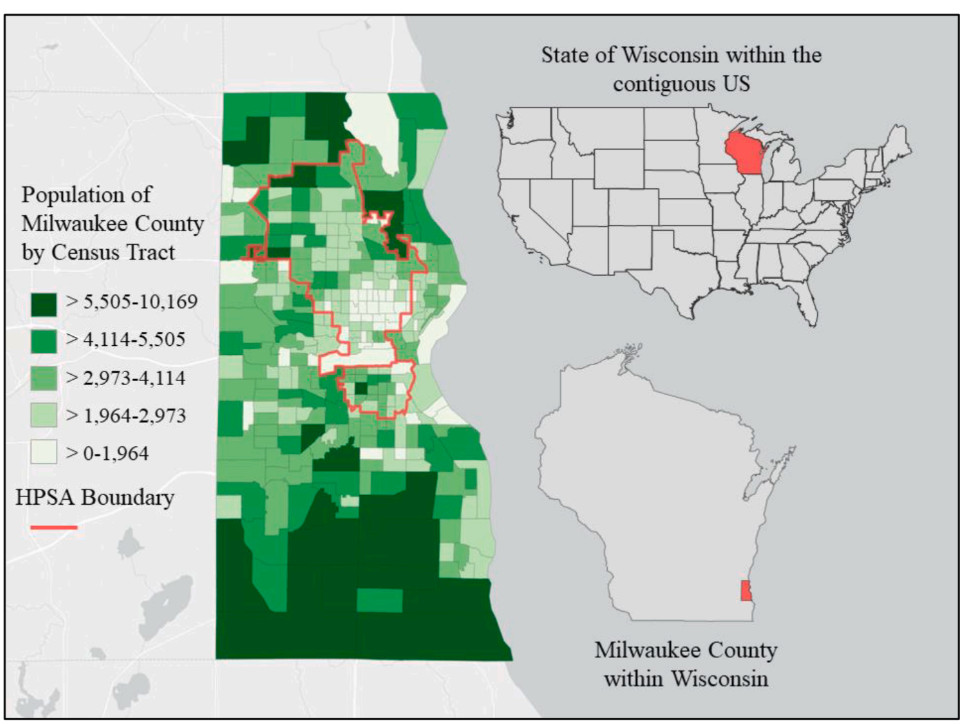

Fig. 1. The study area of Milwaukee County in the State of Wisconsin.

was used to define transit access. This variation in travel time for individuals using public transit is a topic warranting further study.

Modal splits

Modal split estimates for medical and dental trips were derived from the 2017 National Household Travel Survey (NHTS) data. Results were filtered to similarly sized metropolitan statistical areas (MSAs) to represent Milwaukee County. The modal splits and travel times are displayed in Table 1. The Milwaukee MSA, like many others, includes nearby suburban counties, which may skew the survey data in favor of personal vehicles, particularly over transit. A more localized modal survey could improve the accuracy of the findings for future studies. Walking and cycling trips happen over shorter distances and are more likely to be convenient for travelers within a city, while bus trips take significantly longer than personal vehicle trips despite being over shorter distances.

Provider information

For the purposes of this study, the term "family practitioner" was defined to include family doctors, internists, pediatricians, obstetricians/gynecologists, nurse practitioners, and general practitioners. Only facilities that had family practitioners on staff were used in the catchment analysis. Medical facility and practitioner data were collected using the websites of the various health systems in Milwaukee County area (Ascension, Froedtert & the Medical College of Wisconsin, Aurora, ProHealth Care, etc.). Independent practices were collected using online review search services (Yelp, Google Review, Health Grades, Web MD). Facilities were collected within Milwaukee County and in adjacent counties within 30 min of car travel from the Milwaukee County border to account for residents who opt for medical care outside of county lines.

As there is no centralized list of primary healthcare providers in Milwaukee County, several assumptions had to be made when determining the number of providers at non-traditional locations where people may receive primary healthcare. These assumptions include:

Planned Parenthood practices were estimated to have ten family practitioners on staff based on comparisons to similarly sized clinics.

Urgent care facilities without itemized practitioner lists were estimated by collecting total number of urgent care providers employed by the entire health system divided by the number of urgent care locations. This method was also used for government facilities that do not provide practitioner information for specific locations.

Clinics located in pharmacies and convenience stores were estimated to have five family practitioners on staff based on clinics with similar square-footage. The same assumptions were made for private health clinics and facilities for the homeless or uninsured.

It should be noted that practitioners who work at multiple facilities within a single health system were counted at each facility, therefore the number of family practitioners in Milwaukee is likely an overestimation.

Population data

The trip origins used in this study were the population-weighted centroids of each Census tract in Milwaukee County, as is common practice in catchment area analysis. The population estimates came from the American Community Survey (ACS) 2018 5-year estimates. It is likely that the limitations of representing each census tract with one population point affected the pedestrian data, but this was kept for consistency with other methods and modes. Additionally, more origin points would increase the complexity of computation, though future research may find that more distance-sensitive modes of travel warrant that additional effort.

The data sources used in this paper are widely available for locations in the United States, with the collection of primary care facilities being the most challenging step. Primary care facilities were gathered by hand to ensure completeness across a variety of provider networks. Other countries may have access to similar population censuses and modal split data. Results from Milwaukee may be similar to other mid-sized cities, but the unique geographical features, road networks, and modal features (e.g., bus network, facility locations, presence of bike lanes and sidewalks) will affect the results for a given area.

Theory

Evolution of catchment modeling

Catchment models seek to incorporate both supply and demand as well as travel time, which provides a friction factor between the two. The 2-Step Floating Catchment Area (2SFCA) was developed to better identify pockets of low access, but it uses constant weighting within travel time windows and therefore assumes equal access within a catchment (Luo and Wang, 2003). There have been many extensions on this method to address this weaknesses, including the Enhanced 2-Step Floating Catchment Area, a 3-Step method, and others (Luo, 2014; Luo and Qi, 2009; Wan et al., 2012b). Dai introduced a Gaussian-weighted term (Equation (1)) to the 2SFCA model to account for patient's preferences for accessing the closest facility within a catchment window, creating the Gaussian 2-Step Floating Catchment Area (G2SFCA) (Dai, 2010).

$$G(d_{ij}, d_0) = \begin{cases} \dfrac{e^{-0.5\left(d_{ij}/d_0\right)} - e^{-0.5}}{1 - e^{-0.5}}, d_{ij} \le d_0 \\ 0, d_{ij} > d_0 \end{cases} \quad (1)$$

Many catchment models have focused solely on automobile access, though particularly for cities, this does not accurately reflect how people travel. Mao and Nekorchuk introduced transportation modality into catchment analysis by defining different access windows for each mode and weighting the various access values by the proportion of the population utilizing each mode (Mao and Nekorchuk, 2013). Kaur Khakh further built upon this work by creating an improved pedestrian and transit network that accounted for sidewalks, trails, and pedestrian-only pathways (Kaur Khakh et al., 2019). Lin et al. integrated data from the GTFS into their catchment analysis, but analyzed transit and personal vehicles only (Lin et al., 2018). This paper combines the G2SFCA with a modal weighting to do a multimodal analysis that more fully accounts for the various modes used to access primary care in an urban context.

Table 1
Modal information for medical and dental trips (Source: 2017 NHTS).

	Est. Population Split	MOE Pct. (95%)	Median Travel Time (min)	Travel Time MOE (95%)	Trip Distance (mi)	Trip Distance MOE (95%)	N
Personal vehicle[1]	88.73%	5.20%	18	3.67	5.98	0.62	2,231
Bus[2]	5.03%	2.36%	45	38.97	3.11	0.38	59
Walk	1.66%	0.84%	7	9.19	0.49	0.69	45
Bike	0.19%	0.22%	25	80.25	0.62	2.39	7
Other	4.38%	3.38%	15	27.56	3.75	4.1	46

[1] Personal vehicle includes car, SUV, van, pickup truck, motorcycle/moped, RV, and rental car.
[2] Bus includes school bus, public/commuter bus, private/charter/tour bus, and intercity bus.

Because providers will see demand from multiple modes, the first step is to calculate the provider-to-population ratio for each location (R_j). The modal weights are assigned based on the NHTS survey data presented in Table 1. These are used to calculate the demand for each service provider, by weighting the population within each catchment by the modal split as well as the Gaussian friction factor to get a sense of what proportion of each census tract is likely to be served by each provider. The count of family practitioners at each site is used for the supply. The provider-to-population ratio for each destination j is given by Equation (2) as a function of the provider supply (S_j), population of each population center within the catchment (D_k), the modal weight (w_m), and the Gaussian distance weight between k and j.

$$R_j = \frac{S_j}{\sum_m \sum_{k \in \left(d_{kjm} < d_0\right)} D_k w_m G\left(d_{kjm}, d_0\right)} \tag{2}$$

Lastly, the accessibility score is calculated for each population center (i.e., census tract) as a function of the provider-to-population ratios of each destination j within the catchment and the Gaussian weight of the travel time. This value is calculated separately for each mode, so each tract has an accessibility score for car, bike, walking, and transit. For further analysis, this value is normalized to a spatial access ratio (SPAR) by dividing by the mean A_i values across all tracts, both overall and within each mode, as the ratio is less sensitive to the choice of weight and allows for better comparison across tracts (Wan et al., 2012a).

$$A_{im} = \sum_{j \in \left(d_{ijm}, d_0\right)} R_j G\left(d_{ijm}, d_0\right) \tag{3}$$

Selection of travel time thresholds

Selection of the d_0 threshold is an important step in the analysis, as trips longer than this threshold are considered to have no access. Per the definition of HPSAs, 30 min is the threshold for an undue burden of healthcare access and is commonly used in the literature for d_0. Each of the modes covered in this study has different travel time characteristics, so a distribution of travel times from the NHTS sample was used to check the validity of this threshold. As seen in Fig. 2, 75% of personal vehicle, bike, and walk trips for medical/dental visits are 30 min or less, which matches the HPSA value. However, the bus data has a much shallower curve, with only 39% of trips meeting the 30-minute threshold. A 75% threshold for transit data would be 60 min, reflecting the constraints of that mode. This analysis tested both a 30-minute threshold for all modes and a 30-minute threshold for personal vehicle, walking, and biking, with a 60-minute threshold for transit.

Results

Access values were measured for census tracts in Milwaukee County, Wisconsin. The census tracts, population-weighted centroids, and medical facility locations can be seen in Fig. 3. The city is bordered on the east by Lake Michigan and has several rivers running through it, creating geographic obstacles that impact travel times.

Data characteristics of spatial access ratios by mode

As seen in Fig. 4., the access characteristics vary across modes. The personal vehicle results are very tightly clustered, which is to be expected in an urban environment, where many locations may be reached within 30 min. The other modes have a wider range due to the vastly different distances that can be covered in the same amount of time. The median for car, bike, and bus access is close to the mean (1), but it is skewed lower in the pedestrian dataset because of several very strong outliers. Additionally, there are locations with no access via walking or transit, which is important to capture in a larger analysis of access. The bus values are also presented using a time threshold of 60 min to account for longer travel times inherent to that mode.

Maps of results

Map of spatial access ratios within modes

Figure 5 maps each mode's spatial access ratio (SPAR), highlighting the different patterns in within the mode. This SPAR value was achieved by dividing access values by the average access value within each mode's data set. Access is high in downtown and lower at the edges of the county, while transit has gaps created by the availability of bus routes. There is also wider variation in the values for the transit map.

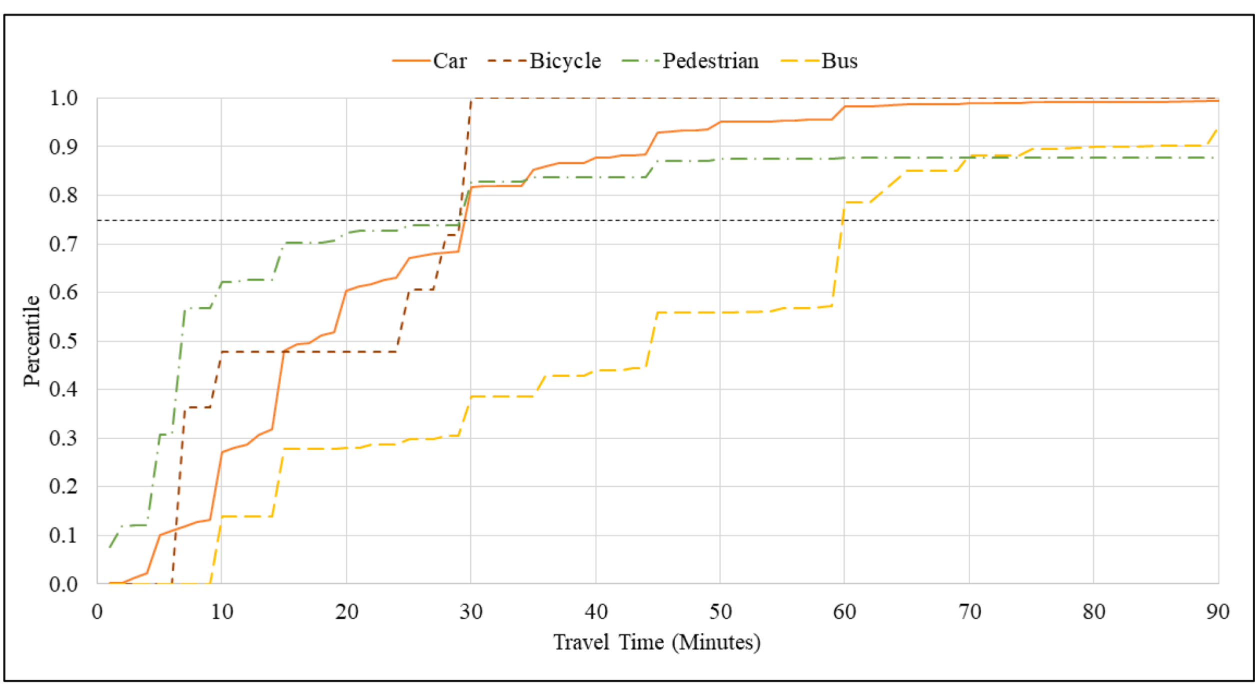

Fig. 2. Travel time distributions for medical and dental trips (Data source: 2017 NHTS).

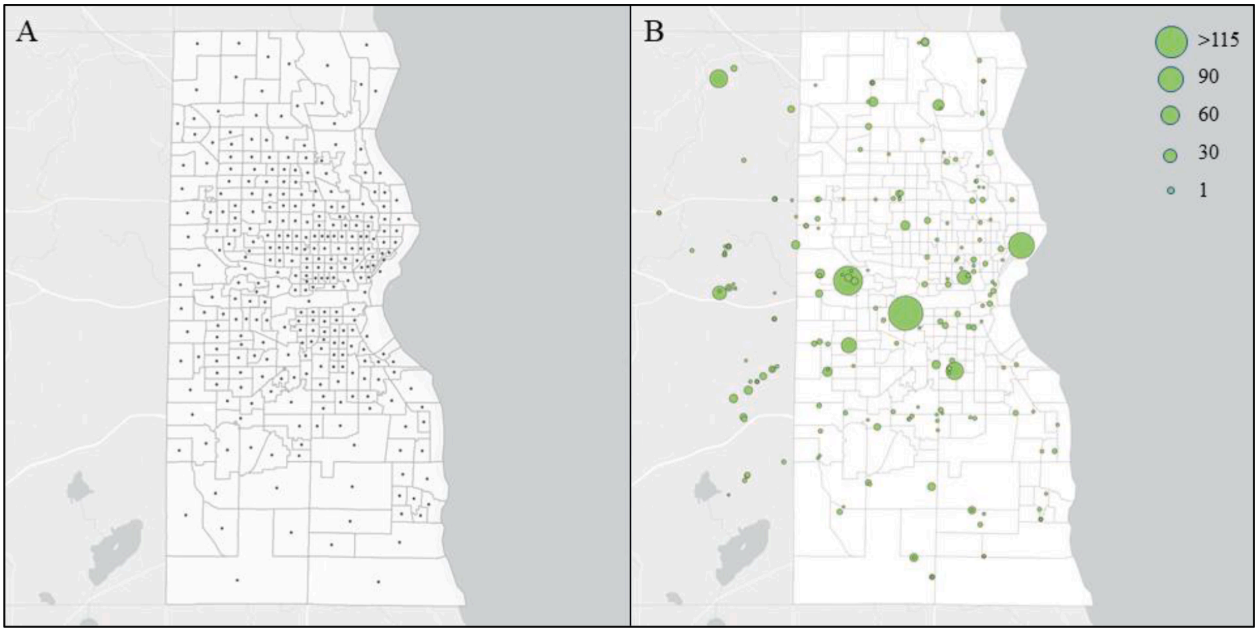

Fig. 3. (A) Census tracts and population centroids, and (B) primary care provider locations and numbers.

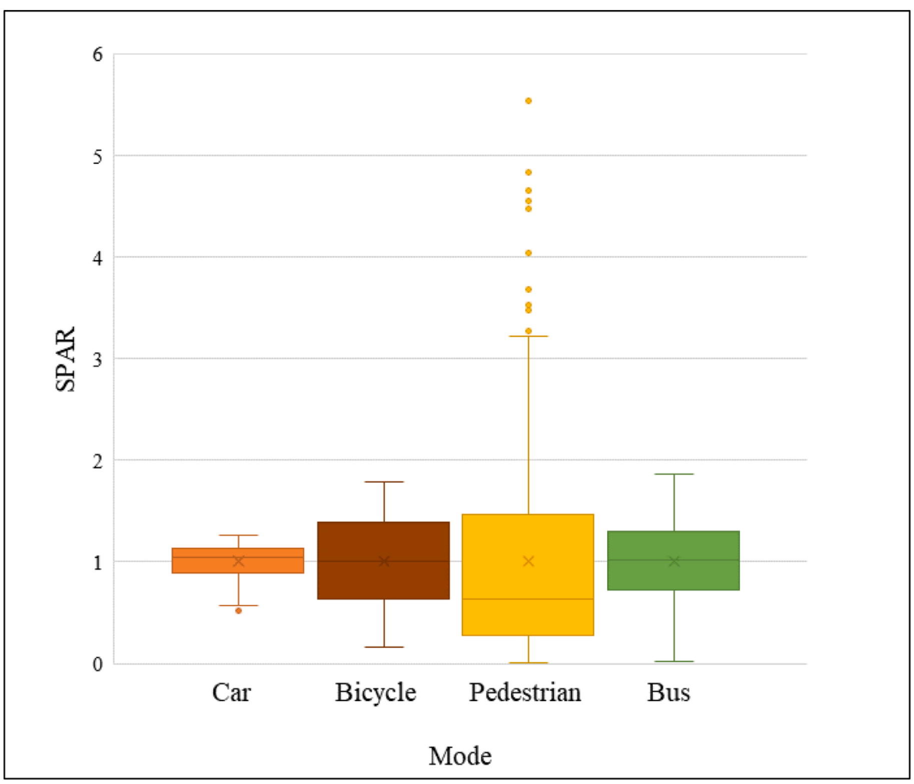

Fig. 4. Comparison of spatial access ratios (SPAR) within modes.

The pedestrian data has the most variation, which is attributable to the much shorter distances covered within 30 min. Tracts of very high access have multiple facilities located in them, and many areas do not have a facility close enough to walk to.

Map of spatial access ratios between modes

Figure 6 shows the spatial access ratio across all modes (SPAR.All), which was calculated by dividing individual access values by the average access value across all mode's data sets. This allows for comparison between modes. Those with personal vehicles have relatively high access throughout the county when compared to other modes. There is high variation in access for transit users, with higher access close to downtown Milwaukee. Most bus routes in the county pass through the downtown area, so higher access in this region is expected. Access values for transit quickly decay beyond the downtown area, with several tracts with no access at the county's north and south boundaries. Cyclists similarly have fair access near the center of the county, while

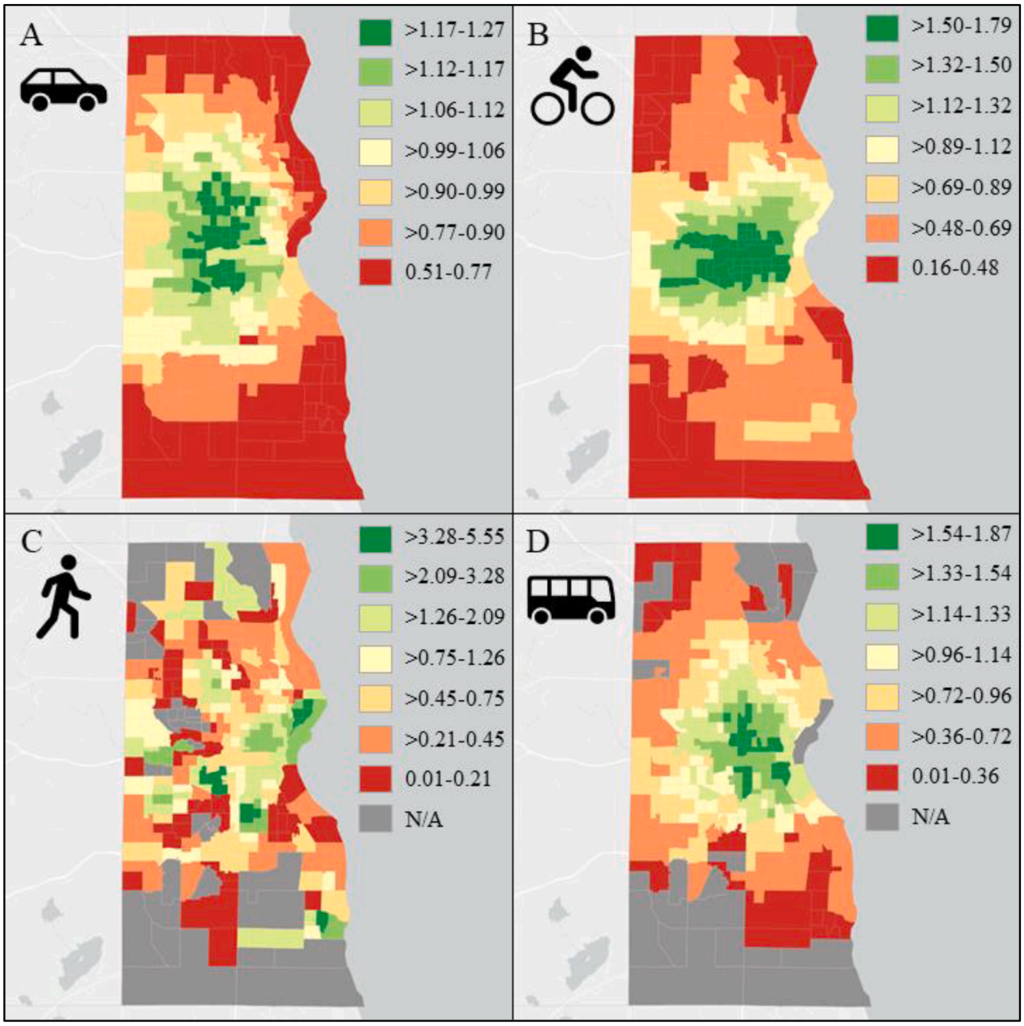

Fig. 5. Maps of SPAR by mode (A) 30-minute car, (B) 30-minute bicycle, (C) 30-minute pedestrian, (D) 60-minute bus.

values gradually decay towards the county's boundaries. Pedestrians experience poor access throughout the county, with several tracts lacking access entirely. It is clear from this comparison that accessibility varies greatly across modes in Milwaukee County, generally favoring those with personal vehicles.

Comparison of travel time thresholds for transit

Figure 7 shows the results for 30- and 60-minute thresholds for transit, to show the limitations of assuming a 30-minute threshold for that mode. There are three tracts which have no access at 30 minutes but do have access within 60 minutes. Also, the larger threshold time smooths out the results radiating outward from the downtown region. For a fair comparison of the equity of modal access however, the 30-minute threshold may be more appropriate as it more accurately shows the difference in not using a car.

Discussion

The results clearly show wide variation in accessibility to primary care facilities based on mode of travel. This is not a surprising result, as each mode studied has a different relationship between time and distance traveled. What the comparison highlights is the additional difficulty in moving around without access to a personal vehicle. Transit trips tend to be longer than comparable car trips, and bike trips rely on both access to a bike and the ability and confidence to ride on surface streets. Pedestrians have very low access across the board, needing to be within a small distance of the destination to be considered accessible.

This work used a multimodal weighting scheme based in NHTS data to account for the population able to access each facility by mode, which serves as the demand in the catchment model. Additionally, travel time measures were done with route-based, open-source information that accounts for transit schedules, safe bike and pedestrian facilities, and elevation changes for non-motorized modes. This allows analysis to be completed easily for a variety of locations with cataloguing the supply locations (e.g., primary care facilities) as the most demanding step.

These results emphasize the need for a multimodal network with a robust public transit system and safe and connected networks of bike and pedestrian facilities. Pedestrian facilities are particularly important as everybody begins and ends each trip as a pedestrian. Expanding access by non-car modes may reduce the need to rely on rides from friends, family, or paratransit.

The catchment results do not directly correlate to current HSPA designations, which weight poverty metrics far more than transportation access in their calculations. Health outcomes also vary across the county when correlated to the catchment results, likely based on other dimensions of access beyond the spatial realm such as affordability and attitudes towards the healthcare system. These differences also account for factors such as income, ethnicity, age, and socio-economic status. This analysis only accounts for spatial access to healthcare and thus does not account for the multifaceted nature of healthcare access.

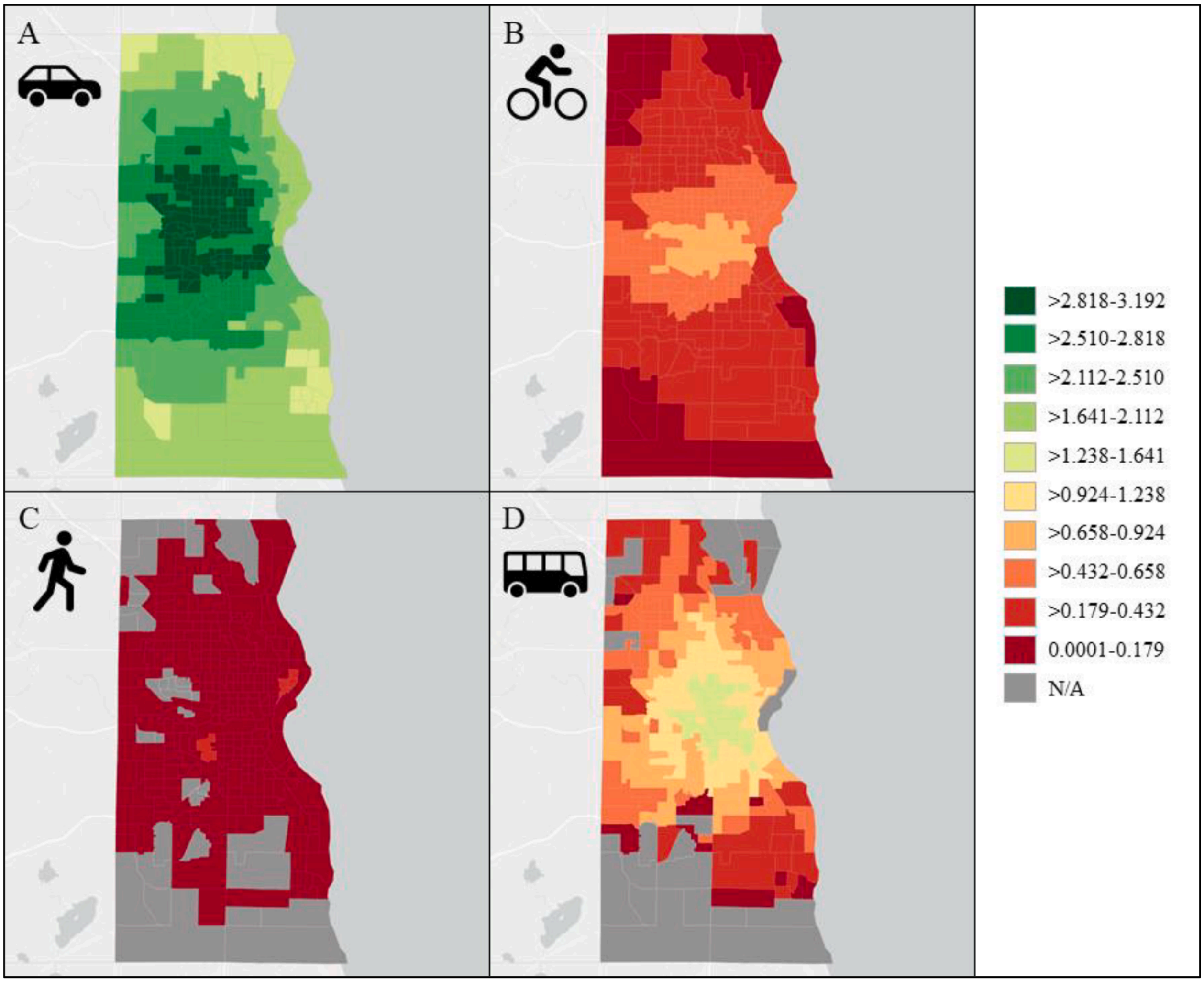

Fig. 6. Maps of SPAR. All by mode (A) 30-minute car, (B) 30-minute bicycle, (C) 30-minute pedestrian, (D) 60-minute bus.

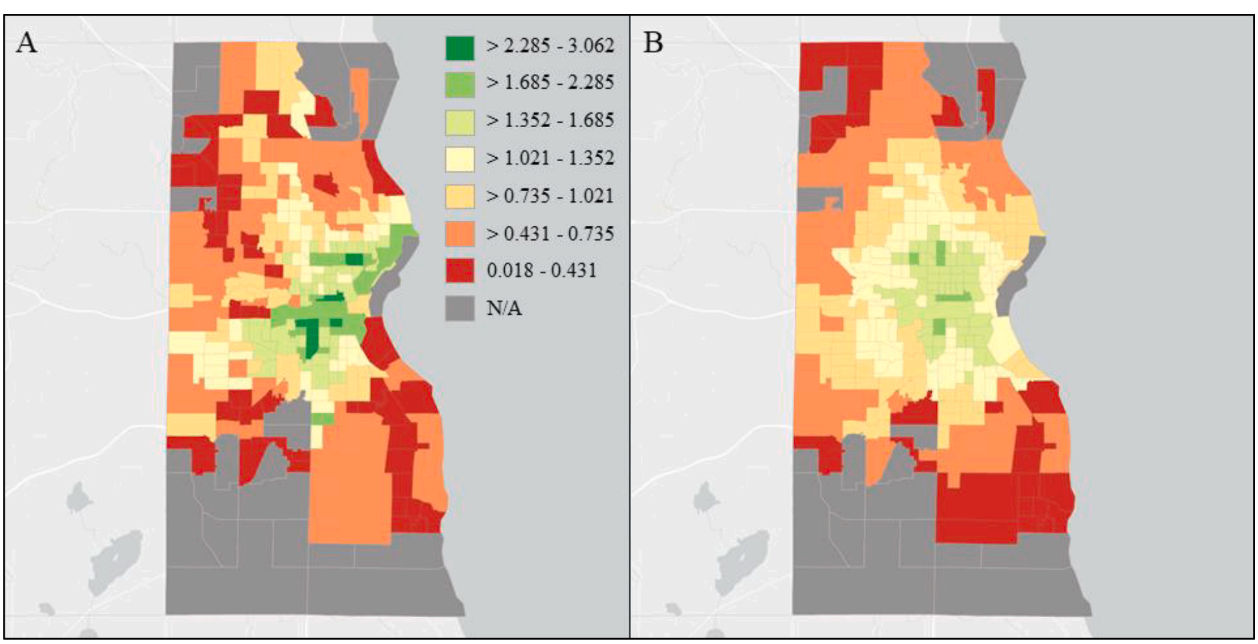

Fig. 7. Comparison of d0 threshold selection for transit (A) 30-minutes, (B) 60-minutes.

Conclusion

The first step to addressing a problem is measuring it. For the issue of spatial access to primary care facilities, we have incorporated multi-modal data through open-source data sets to capture a variety of travel behaviors. The results highlighted disparities among modes in the ability to access primary health care, which impacts quality of life and overall health.

There are many other facets beyond transportation that affect both access to health care (e.g., insurance, cost, accommodation) and mode choice (e.g., availability of a car, walking ability). Future work will focus specifically on populations that do not have regular access to a vehicle to better study how they travel and how that impacts accessibility. Identifying gaps in access will allow for better targeting of transportation services and other outreach solutions to improve mobility. Improving access measurement may also inform the identification of HSPAs in the future. Better understanding of the time–space dimension of transit access will also inform trip planning and improved comparison to other modes. Further research can dig into the different characteristics of each mode and determine how to more accurately model access patterns, as shown here with the larger threshold for transit access.

CRediT authorship contribution statement

Danielle E. Del Conte: Investigation, Validation, Visualization, Writing – original draft. **Amanda Locascio:** Investigation, Visualization, Writing – review & editing. **Joseph Amoruso:** Investigation, Writing – review & editing. **Margaret L. McNamara:** Conceptualization, Methodology, Software, Supervision, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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