Equitable Access to Urgent Care: Examining Transportation Inequities and Social Vulnerabilities in Chicago through GIS

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Abstract

Urgent care centers are essential for providing lower-cost treatment for non-critical conditions that otherwise overwhelm emergency departments. Unlike ambulances and emergency departments (EDs), which often have long wait times and prioritize life-threatening cases, urgent care offers the "right level of care". Urgent care centers can be valuable for vulnerable populations with limited access to primary care by providing timely, lower-cost treatment. Geographic accessibility of urgent care, measured through travel time and social vulnerability indices (SVI), remains understudied compared to primary care and ED access. We analyze urgent care accessibility across Chicago census tracts (n = 856) and urgent care facility locations (n = 27) with generalized linear mixed effects models (GLMEM), to evaluate how travel time and social vulnerabilities contribute to inequities in urgent healthcare access. Our results show that access varied substantially by transportation mode, with car travel providing widespread coverage. Reliance on public transit or walking also revealed disparities for socially vulnerable populations. These findings demonstrate how transportation inequities shape urgent care access and help to guide efforts toward equitable healthcare planning.

CCS Concepts

• **Applied computing** → **Health informatics**; • **Information systems** → **Geographic information systems**; • **Social and professional topics** → Geographic characteristics.

Keywords

Healthcare Access, Urgent Care, Transportation Inequity

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1 Introduction

In the United States, lack of transportation is a major barrier to healthcare access. More than one in five adults without a vehicle or access to public transit goes without healthcare, even though they needed it [31]. These transportation inequities disproportionally affect socially disadvantaged: low-income, elderly, or chronically ill. The lack of reliable transportation leads to missed medical appointments, delayed care, worse chronic disease outcomes [33, 40], and disproportionate emergency department (ED) use.

Disproportionate reliance on EDs is a consequence of these access barriers. National data indicates that vulnerable populations, especially those who are lower-income, uninsured, or do not have reliable vehicle or internet access, make significantly more preventable ED visits [7, 36]. At the community level, low-income urban residents face barriers to accessing primary healthcare (PHC) and often choose the ED for non-urgent treatment, due to the perception that EDs are more accessible [39]. Ambulance transport often becomes the solution for patients without private transportation. However, it is not an effective replacement for urgent or PHC access [12], as Medicare only covers ground ambulance services when transport is deemed medically necessary. Ambulances are costly, with nearly half of emergency ground ambulance rides for privately insured patients generating out-of-network charges [4, 29]. Beyond their financial burden, over-reliance on ambulance transport contributes directly to ED congestion. Facilities are already overcrowded and ambulance offload delays further exacerbate system strain [12, 20].

In contrast, urgent care centers already provide a more accessible and cost-effective alternative for patients with non-life-threatening conditions. On average, EDs are about 10 times as expensive as urgent care centers: urgent care visits cost around \$164-\$178, whereas the same diagnosis treated at an ED would cost around \$1,400-\$2,200 [3, 14]. Using urgent care for lower-acuity conditions instead of the ED has been found to reduce ED use and overcrowding substantially among Medicaid users and uninsured. The reduction in ED use was observed across acuity levels, which eased pressures on hospital systems and resources [2, 3, 28]. Urgent care centers have a critical role in providing primary and emergent care, but access to urgent care is not equitable. Location, neighborhood-level socioeconomic factors, and transportation options all determine whether patients can effectively reach healthcare facilities like EDs and PHC [33, 39, 40], but little work has examined how transportation barriers and community vulnerability shape urgent care accessibility.

This paper contributes to health equity and geography research by empirically mapping transportation-based disparities in access to urgent care centers, a setting that has received little attention compared to primary care and emergency departments. We quantify how social vulnerability and transportation modalities (car, public transit, walking) shape urgent care accessibility when measured by travel times rather than geographic distance. We also identify spatial and demographic patterns in accessibility, including the disproportionate burden on communities, particularly those with higher socioeconomic vulnerability, older populations, and

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single-parent households. By integrating urgent care access into the broader healthcare accessibility literature, this work extends current understanding of how transportation barriers drive inequities in non-emergent, urgent care utilization. We analyze travel time to urgent care facilities with multilevel modeling and social vulnerability indicators, providing a framework for understanding how geographic and social vulnerabilities influence urgent care accessibility across spatial and community level inequities.

2 Background

Access to healthcare has long been recognized as unevenly distributed across populations, shaped by the geographic availability of providers, and the social and demographic vulnerabilities of the communities they serve. Research illustrates that transportation barriers contribute to delayed care and increased reliance on EDs. In a systematic review of 61 U.S. studies [33], researchers found that the lack of transportation poses a significant barrier to primary and chronic condition care, where 10%-51% of patients reported to be affected. Children in low-income families, elderly adults, minorities, and rural residents were most affected. These groups sustained unmet care, often due to lack of access to a car, cost of transit, or difficulty finding a ride. While evidence from this study suggested that distance alone may not represent the full impact of transportation barriers, other studies demonstrate that transportation barriers disproportionately affect vulnerable groups and contribute to poorer management of chronic disease and widening health disparities [18, 31, 40, 41]. In the analysis of the National Health Interview Survey (1997-2017), it is estimated that 5.8 million Americans delayed medical care in 2017 due to lack of transportation [40]. These transportation barriers disproportionately affected Hispanic adults, those living below the poverty threshold, Medicaid recipients, and individuals with functional limitations, even after adjusting for sociodemographic and health factors. Additionally, the study emphasizes that vulnerable populations are still at a heightened risk for delayed care, treatment, and reliance on expensive ED services, despite having existing benefits in place.

The effects of transportation on healthcare accessibility can be measured through geographic proximity to facilities with distance (e.g., Euclidean or street-network distance) or density of available providers. In a study of vaccination access in Chicago, access was measured as the street-network distance from each population-weighted census tract centroid to the nearest site, with access defined as living within one mile [22]. In a study of primary healthcare access in Albuquerque, access was measured by travel time rather than distance, defining service areas as 30 minutes by car and 60 minutes by bus from census block group centers [18].

While inadequate transportation due to geography is a barrier, community-level factors such as poverty, disability, household composition, and housing conditions, interact with transportation to shape healthcare access. To capture these intersecting factors of social vulnerability, the CDC's Social Vulnerability Index (SVI) provides a standardized measure of community resilience under health and environmental stressors [6]. SVI scores reflect social vulnerabilities using four main categories: socioeconomic status, household composition & disability, minority status & language, and housing & transportation [34], where a higher score meant more vulnerability. These categories are further broken down into different factors of social vulnerabilities (Figure 1).

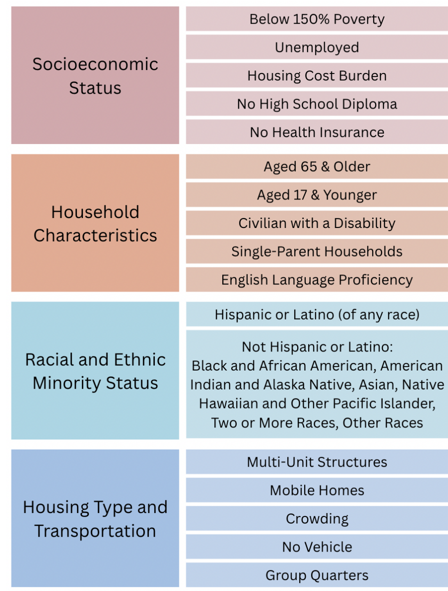

Figure 1: Overall social vulnerability framework, illustrating the four themes and their component variables.

SVI was originally designed for natural disaster preparedness, but more recently, also used for identifying populations at risk for unmet medical needs and poor patient outcomes in epidemiology and healthcare research. For example, higher SVI scores were associated with worse outcomes in surgery patients [10] and postoperative care [11, 32]. SVI has also been applied to population-level cancer outcomes. In a national cross-sectional analysis of more than 3,000 U.S. counties, it was found that counties with higher SVI scores had significantly lower breast and colorectal cancer screening rates, higher incidence of colorectal and lung cancers, and consistently higher mortality across breast, colorectal, and lung cancers [26]. SVI has been linked to issues in healthcare access for people with chronic disease. In a study of over 200,000 adults with atherosclerotic cardiovascular disease, it was found that individuals in states with the highest SVI had significantly higher odds of lacking a primary care clinician, delaying care, being unable to see a doctor due to cost, and experiencing cost-related medication nonadherence, compared to those in the lowest SVI states [35].

Studies demonstrated that the SVI is a widely used and validated framework for analyzing inequities in healthcare[18, 22, 35]. Much of the literature is focused on primary care, emergency departments, or specialized services, whereas urgent care access has received less attention, despite its growing role in healthcare [2, 3, 14]. Urgent care centers reduce ED burden, lower costs, provide access for vulnerable populations, while offering faster and more affordable treatment. In this paper, we focus on urgent care accessibility and contribute an empirical analysis of multimodal travel times linked with community-level vulnerability using the CDC's Social Vulnerability Index. We seek to shed light on how transportation barriers and social conditions shape access to urgent care and to identify where inequities in accessibility remain across communities.

3 Methodology

This study examined transportation access of urgent care facilities, using SVI and socioeconomic data at the census tract level (n = 856 tracts). 27 urgent care facilities in Chicago were studied.

3.1 Data

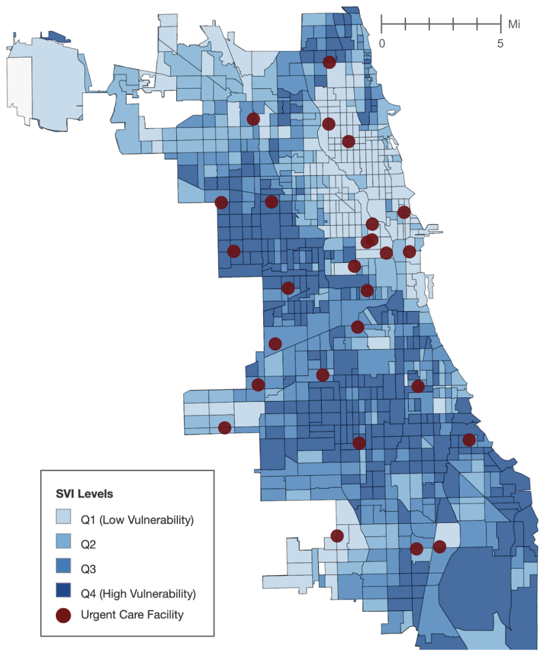

Figure 2: Social vulnerability index graph of Chicago by census tract, with urgent care locations. CDC's SVI uses quartiles from Q1: 0 to 0.25, Q2: 0.25 to 0.50, Q3: 0.50 to 0.75, and Q4: 0.75 to 1.0, where Q1 is the least vulnerable and Q4 is the most vulnerable.

Chicago's geographic boundaries were defined using ArcGIS shapefiles [8], and census tract boundaries were drawn from the 2022 U.S. Census Bureau TIGER/Line dataset [38]. Only tracts falling within the city limits were retained for analysis. Urgent care facility locations were identified through the NASA Center for Climate Simulation (NCCR) Public Health API [15]; after filtering to those within Chicago, 27 facilities remained. Socioeconomic and demographic information came from the U.S. Census Bureau's American Community Survey (ACS) 5-Year Estimates [37], providing tract-level data on unemployment, disability, age 65 and older, housing burden (defined as >30% of income spent on housing), single-parent households, and limited English proficiency. These measures served as key indicators in the GLMEM regression models. To capture broader community vulnerability, we incorporated Social Vulnerability Index (SVI) scores from the Centers for Disease Control and Prevention (CDC) and the Agency for Toxic Substances and Disease Registry (ATSDR) 2022 release for Illinois census tracts [5]. Figure 2 illustrates the spatial distribution of SVI scores across Chicago with the locations of urgent care facilities.

The additional demographic and socioeconomic variable "no vehicle access" was initially tested but ultimately excluded from the final models due to concerns about multicollinearity and conceptual overlap with both the transportation mode outcomes (walking and transit times) and other SVI housing/transportation indicators. Because the lack of vehicle access is strongly correlated with greater reliance on non-car modes [17], its inclusion risked redundancy in the models. Additionally, census tracts with no travel time data for any transportation mode were filtered out, and missing or invalid geometry data were removed from the dataset.

3.2 Accessibility and Geographical Modeling

With the Google Maps Distance Matrix API [13], distances and time traveled were calculated between the centroids of each census tract and all urgent care centers across Chicago. The API was used to obtain times for multiple transportation modes: driving, public transit, and walking. Travel times were grouped into 10-minute intervals, ranging from 10 to 60 minutes. For each mode of transportation, each census tract was categorized into one of these intervals, if one could travel to any urgent care within one of those intervals. Travel times to urgent care centers were used as opposed to distance alone because travel times can represent real-world conditions, transportation options, traffic, and urban barriers, whereas euclidean road distance does not [9, 23].

To address how travel times were associated with community characteristics, the travel time data were integrated with SVI scores at the census tract level. The CDC SVI and ACS Socioeconomic and demographic datasets were combined by mapping GEOIDs of SVI data to census tracts to link demographic data to geographic boundaries. SVI data was spatially joined with census tract boundaries using the unique GEOID (Geographic Identifier) that links demographic data to geographic boundaries. This integration created a unified spatial dataset where each census tract contained both its geometric boundary information and its corresponding SVI score. The SVI scores were then categorized into quartiles (Q1 = low vulnerability to Q4 = high vulnerability) as predictors in the GLMEM models. To illustrate the distribution of selected variables from the SVI framework that were included as predictors in the regression models, Figure 3 shows normalized values for four indicators: population ages 65 and older, single-parent households, population aged 17 and under, and population with disability. These highlighted variables represent key components of the household composition and disability domain and consistently emerged as significant predictors across multiple transportation modes.

3.3 Spatial Analysis

GLMEM with fixed and random effects were conducted to examine the impact of census tract–level sociodemographic characteristics (e.g., unemployment rate, population with disabilities, population 65 and older, housing cost burden, single parents, limited English proficiency) and composite measures of social vulnerability on spatial access to urgent care facilities by car, public transit, and walking.

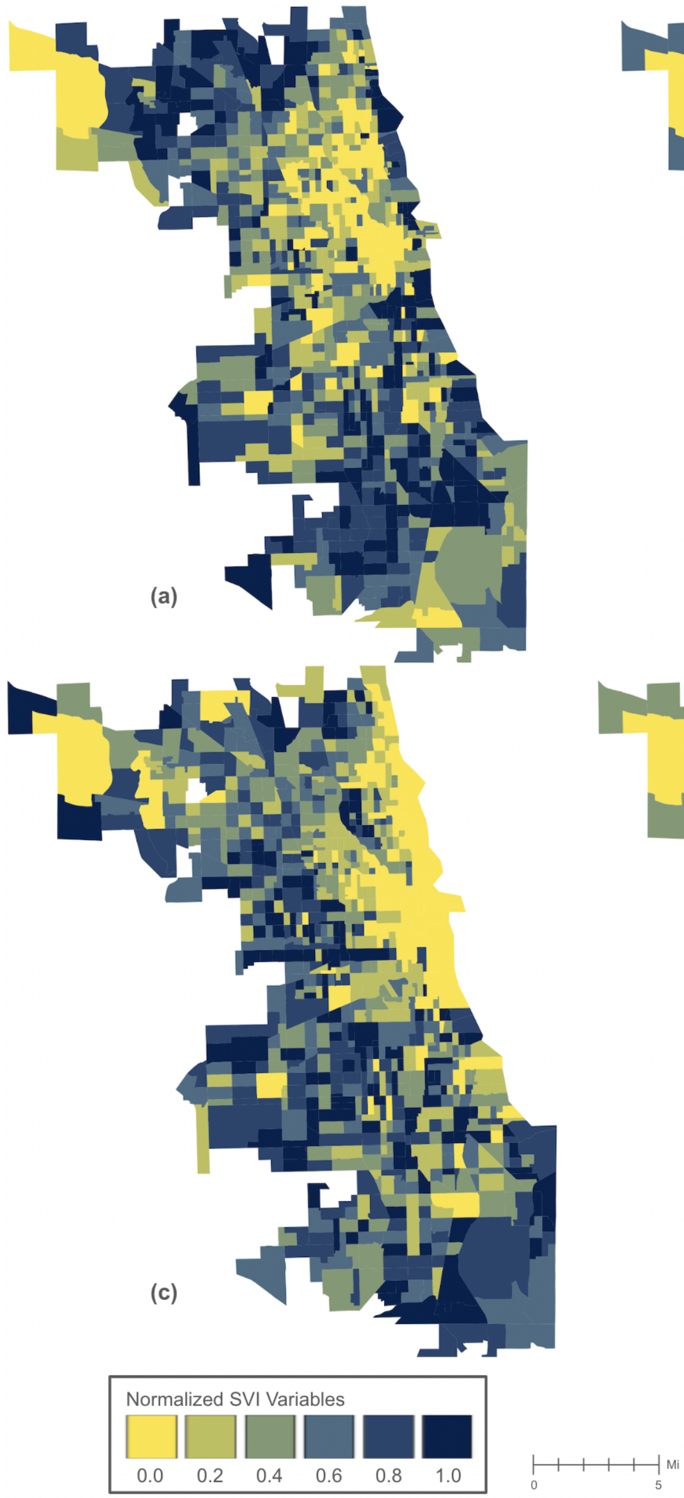

Figure 3: Normalized distributions of selected SVI variables. Values are scaled from 0.0 to 1.0, with 0.0 indicating the lowest level of relative vulnerability and 1.0 indicating the highest. **SVI variables**: (a) population aged 65 and older, (b) single-parent households, (c) population aged 17 and under, and (d) population with disability.

Fixed and random effects models were used to account for the clustered and correlated structure of the data, where multiple travel modes are nested within census tracts and observations share unmeasured spatial and contextual factors that violate independence assumptions[27]. Because individuals are shaped by their environments (e.g., neighborhoods, clinics) and other underlying infrastructure factors, nearby observations may be correlated. This illustrates how the independence assumption of standard regression is often unrealistic in public health, whereas multilevel modeling reveals interactions between individual and group-level predictors [19, 21].

Analyses were conducted using Restricted Maximum Likelihood (REML) estimation. REML was used because it accounts for the degrees of freedom lost, provides less biased and more reliable variance estimates, and shows reduced bias in finite samples[24, 25]. The car, transit, and walking times to urgent care centers were standardized. This allows for the interpretation of coefficients as changes in travel time per standard deviation change. All analyses were performed using Python (version 3.13.3) with the statsmodel library (version 0.14.5) [16].

4 Results

We examined geographic accessibility to urgent care facilities across Chicago census tracts for variations by transportation mode and community characteristics. First, we compared travel time to urgent care centers across three transportation modes: car, public transportation, and walking. Next, we investigated differences in time required to reach urgent care by transportation mode and associations with sociodemographic and social vulnerability indicators.

4.1 Geographic Accessibility to Urgent Care Facilities

Travel times to the nearest urgent care facility varied widely by transportation mode. Travel time by car was significantly quicker and more consistent than using public transportation or walking, with an average of 7.82 ± 3.45 minutes. Public transit required considerably more time, averaging 20.22 ± 14.36 minutes, and showed much greater variability. Walking was the slowest mode of transportation, with trips averaging 42.34 ± 31.99 minutes and the greatest variation in duration. On average, transit trips were nearly three times longer than car trips, while walking trips were more than five times longer. Full descriptive statistics by mode are shown in Table 1.

Table 1: Travel Times to Urgent Care by Mode

Mode	Mean (min)	Median (min)	Min	Max	SD (min)
Car	7.82	7.45	0.43	27.83	3.45
Transit	20.22	18.20	0.80	242.38	14.36
Walking	42.34	37.51	0.80	309.82	31.99

Geographic access to urgent care was found to be significantly higher by car than by public transportation or walking, as illustrated in Figure 4. Travel by car had the most access, with 78.4% of tracts reachable within 10 minutes and near-universal coverage (99.6%) by 20 minutes. For public transport and walking, only 11.5% of tracts were accessible by transit and 5.5% by walking within 10 minutes. Transit access expanded quickly beyond 20 minutes, covering nearly all tracts by 40 minutes. Access was not the same for walking: travel times were considerably longer in comparison to public transit and car. Population-level access followed a similar pattern. At 10 minutes, 73.6% of the population was reachable by car, compared to 10.9% by transit and 6.5% by walking. By 20 minutes, car access included 99.6% of residents, while transit and walking reached 54.8% and 18.2%, respectively. By 30 minutes, transit covered 86.5% of the population and walking 34.5%.

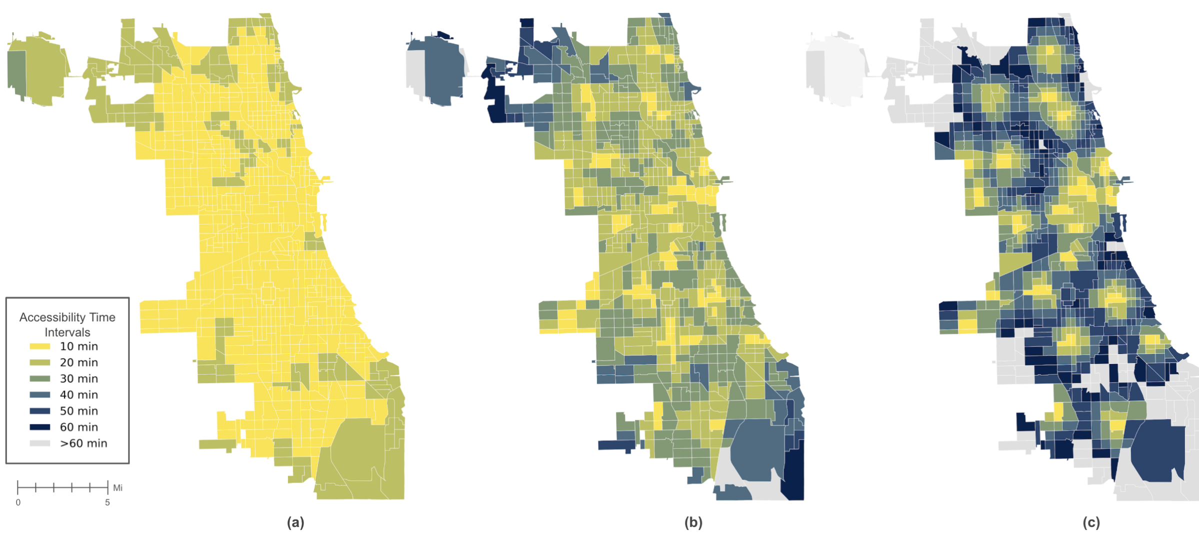

Figure 4: Accessibility to urgent care by travel time across three transportation modes
Panels show estimated travel times to the nearest urgent care facility by **(a)** car, **(b)** public transportation, and **(c)** walking.

4.2 Multilevel Socioeconomic

Multilevel regression models identified several sociodemographic and housing characteristics associated with longer travel times to urgent care, with patterns varying by transportation mode (Table 2).

Walking access to urgent care showed the strongest and most variable associations with community characteristics. Census tracts with higher proportions of older adults had substantially longer walking times (β = 5.896, SE = 0.890 [4.152, 7.640]), where β represents the estimated regression coefficient, *SE* is the standard error, and the bracketed values indicate the lower and upper limits of the 95% confidence interval, respectively. Tracts with more children under 17 years also had longer walking times (β = 5.657, SE = 0.969 [3.757, 7.556]). Single-parent households were also strongly associated with longer walking travel (β = 3.696, SE = 0.984 [1.766, 5.625]), alongside disability prevalence (β = 2.095, SE = 1.023 [0.090, 4.101]). In contrast, the only factor consistently linked to shorter walking times was the presence of multi-unit housing, which significantly reduced walking travel (β = -3.357, SE = 0.400 [-4.141, -2.573]).

Car travel times were generally short, yet several sociodemographic indicators remained significant. Older age was associated with increases in car travel duration, where ages 65+ were linked to longer travel times to urgent care (β = 0.676, SE = 0.017 [0.643, 0.709]). Similarly, households with children under 17 (β = 0.497, SE = 0.072 [0.357, 0.638]), limited English proficiency (β = 0.275, SE = 0.028 [0.222, 0.329]), and housing burden (β = 0.276, SE = 0.113 [0.055, 0.496]) were associated with longer access times. Mobile homes, although less common in urban tracts, were associated with notably longer car travel (β = 0.555, SE = 0.005 [0.546, 0.563]).

Transit access reflected patterns distinct from walking or car. Census tracts with higher proportions of children under 17 (β = 1.928, SE = 0.448 [1.049, 2.807]) or larger older adult populations (β = 1.810, SE = 0.464 [0.901, 2.720]) faced substantially longer transit times. Single-parent households β = 1.718, SE = 0.461 [0.814, 2.621]) and mobile homes (β = 3.821, SE = 0.390 [3.056, 4.586]) were also positively associated. In contrast, like walking times, multi-unit housing was negatively associated with transit travel times, reducing travel by -1.251 minutes per standard deviation (β = -1.251, SE = 0.432 [-2.098, -0.404]).

Poverty (150% of federal poverty guideline) and unemployment were not significant across walking, car, or transit travel times. For walking travel time, limited English and housing burden was not found to be significant; for car travel time, no high school diploma, single-parent households, and disability were not significant; and

Table 2: Predictors of Changes in Urgent Care Travel Time by Transportation Mode Standard Coeff. (β) represent fixed-effect regression coefficients. SE = standard error. CI = 95% confidence interval. Positive coefficients indicate longer travel times; negative coefficients indicate shorter travel times.

Variable	Standard Coeff.	SE	95% CI (Lower, Upper)		p-value
Walking					
No High School Diploma	2.167	1.015	0.178	4.156	0.034
Age 65 and Over	5.896	0.890	4.152	7.640	<0.001
Age 17 and Under	5.657	0.969	3.757	7.556	<0.001
With Disability	2.095	1.023	0.090	4.101	0.039
Single Parent	3.696	0.984	1.766	5.625	<0.001
Limited English	1.920	0.768	0.415	3.425	0.012
Multi-Unit Housing	-3.357	0.400	-4.141	-2.573	<0.001
Mobile Homes	10.315	0.152	10.018	10.613	<0.001
Car					
Poverty (150%)	0.027	0.002	0.023	0.030	<0.001
Housing Burden	0.276	0.113	0.055	0.496	0.014
No High School Diploma	0.110	0.048	0.016	0.203	0.022
Age 65 and Over	0.676	0.017	0.643	0.709	<0.001
Age 17 and Under	0.497	0.072	0.357	0.638	<0.001
With Disability	0.220	0.005	0.212	0.229	<0.001
Single Parent	0.167	0.021	0.126	0.207	<0.001
Limited English	0.275	0.028	0.222	0.329	<0.001
Multi-Unit Housing	0.030	0.011	0.009	0.051	0.004
Mobile Homes	0.555	0.005	0.546	0.563	<0.001
Overcrowding	0.263	0.025	0.213	0.313	<0.001
Group Quarters	0.098	0.011	0.075	0.120	<0.001
Transit					
Age 65 and Over	1.810	0.464	0.901	2.720	<0.001
Age 17 and Under	1.928	0.448	1.049	2.807	<0.001
Single Parent	1.718	0.461	0.814	2.621	<0.001
Multi-Unit Housing	-1.251	0.432	-2.098	-0.404	0.004
Mobile Homes	3.821	0.390	3.056	4.586	<0.001

for transit travel time, housing burden, no high school diploma, limited English, and disability showed no significance. SVI quartiles were found to be insignificant, likely due to overlap with individual socioeconomic indicators and multicollinearity among variables. Census tracts were tested in parallel specifications and were not found to be statistically significant in any mode.

The GLMEM models use the specification where travel time is predicted by standardized socioeconomic indicators, with census tracts as random intercepts. No random slopes or cross-level interactions were tested in these models. The models achieved convergence with REML estimation, and model comparisons were not conducted, as the mixed effects structure inherently accounts for the nested data structure and spatial dependencies [19, 21, 27].

5 Discussion

The purpose of this study was to examine how transportation mode and community-level vulnerability shape access to urgent care in Chicago. We found that travel times by car were short and consistent, but reliance on public transit or walking substantially extended travel times and reduced accessibility. These findings build on prior evidence that transportation barriers negatively affect socially vulnerable groups [33, 40] and extend this understanding to urgent care, which has received less attention than primary care or ED research. Consistent with prior studies of PHC [18, 22], we find that measuring accessibility by travel time rather than distance reveals more pronounced inequities. Although 99.6% census tracts could reach urgent care within 20 minutes by car, less than two-thirds of residents were reachable within the same time frame by public transit, and less than one in five by walking.

This suggests that facility placement alone is insufficient to guarantee equitable access: the transportation network and built environment critically shape whether urgent care is a realistic option [1]. The regression models highlight specific sociodemographic factors, namely older age, children in the household, single-parent households, and disability, are consistently associated with longer travel times. These patterns may reflect limited mobility, dependence on non-car modes, and neighborhood disinvestment, which together exacerbate barriers to urgent care. In contrast, multi-unit housing was linked to shorter travel times across modes, likely reflecting denser urban areas where urgent care sites cluster. These findings echo prior work on ED reliance in low-income urban residents, who often perceive EDs as more accessible [39]. This illustrates that due to the misconception of accessibility of EDs, transportation barriers may push households with higher needs away from urgent care.

Prior studies have noted that vulnerable populations are more likely to rely on non-car modes of transportation [33, 40], but these modes substantially increase travel time and reduce realistic access to healthcare. To address these disparities, local governments, health public officials, and urban planners should consider strategies that improve public transit coverage and reliability, particularly in high-SVI neighborhoods, as well as incentivize urgent care siting in socially vulnerable areas. Such measures are likely to expand equitable access to urgent care and reduce preventable reliance on emergency departments [30].

Travel times were measured from census tract centroids rather than individual addresses, which may mask within-tract variation. The Google Maps Distance Matrix API reflects typical traffic and transit conditions but does not capture delays, schedule gaps, or peak-hour variability. The API is a commercial platform with query limits and usage costs, which can restrict large-scale or high-frequency analyses, and contains proprietary routing algorithms and mode assumptions that may differ from lived travel behavior, introducing potential bias in estimated travel times. Second, this study used direct travel time modeling as a baseline measure of accessibility to provide comparison across modes. While more advanced models for spacial accessibility exist, such as multi-modal floating catchment area (FCA) models or regional accessibility assessment models (RAAM), these approaches require more detailed provider capacity and data that were beyond the scope of this analysis. Third, the study was cross-sectional and focused on a single urban area. Because the analysis was limited to Chicago's city boundaries, census tracts located near the municipal border may be subject to border bias. This limits generalizability to rural or suburban settings in other parts of the world. Fourth, urgent care centers are less systematically documented than hospitals or federally qualified health centers, and the dataset used here may omit facilities or misclassify other walk-in clinics. Given the rapid turnover and variability in urgent care reporting, the NASA urgent care database [15] may not fully represent the true distribution of access. Fifth, while mixed effects models accounted for clustering, other unobserved factors, such as provider acceptance of insurance, clinic hours, or perceptions of safety, which were not captured in these datasets, may also influence practical accessibility. To address these limitations, future work could expand this analysis across diverse urban and rural regions and incorporate spatiotemporal dynamics to assess whether similar inequities persist. Linking geographic accessibility with utilization data could clarify whether inequities in travel times directly affect urgent care use and substitution for ED visits. Finally, qualitative studies with community members in high-SVI neighborhoods could provide insights into how transportation barriers interact with perceptions of urgent care availability.

6 Conclusion

This study corroborates that urgent care accessibility is unevenly distributed across Chicago by both transportation mode and social vulnerabilities. In Chicago, car travel offered near-universal access to urgent care within short time frames, but reliance on public transit or walking significantly lengthened travel times and restricted realistic accessibility. These disparities disproportionately affect socially vulnerable communities, particularly those with higher proportions of older adults, children, single-parent households, and residents with disabilities. This also illustrates how transportation infrastructure and social determinants of health can affect access to healthcare.

By integrating multimodal travel times with social vulnerability indicators, our analysis shows that accessibility is not only a matter of facility placement but also of the broader transportation network and built environment. Urgent care availability cannot relieve pressure on emergency departments if vulnerable populations cannot reach these facilities. Addressing inequities will therefore require coordinated strategies that include expanding public transit reliability, incentivizing urgent care placement in high-vulnerability neighborhoods, and aligning urban planning with community health needs. The findings extend the healthcare accessibility literature by situating urgent care within the framework of transportation-based inequities. Addressing inequities in urgent care requires attention not only to where facilities are located but also to how different communities are able to reach them.

Future research could explore how changes in transit systems, emerging mobility options, and telehealth integration could reshape urgent care accessibility. Such work can inform policies that ensure more equitable healthcare access in rapidly evolving urban environments.

Author Disclosure: The authors used generative AI tools (ChatGPT and Cursor) to improve the readability of certain paragraphs, assist with table formatting, and provide coding support during data analysis, in accordance with ACM publication guidelines. All text, tables, and code were written, reviewed, and verified by the authors to ensure accuracy, originality, and alignment with the research findings.

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