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Evaluating Spatial Access to Healthcare Centers in a Subsection of Southern Chicago

Samuel Dadson[1]

[1]Western Illinois University

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ABSTRACT

This project evaluates spatial accessibility to healthcare facilities across seven adjoining neighborhoods in Southern Chicago using a multimodal network analysis and location-allocation modeling. The objective was to identify disparities in access and propose optimal facility locations that promote spatial equity, especially for underserved populations. Three demand weighting scenarios were analyzed: binary low-income status, total population, and a composite equity demand field. Each scenario was evaluated using the "Minimize Impedance" location-allocation method and a multimodal network incorporating walking and driving. Facilities were ranked based on total demand captured. Results show that the existing facilities poorly serve walkable populations and that new optimized sites significantly improve equitable access. This analysis demonstrates the effectiveness of GIS in data-driven facility planning to improve healthcare equity and advance socially just urban development.

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CHAPTER ONE
INTRODUCTION

Access to healthcare is a fundamental component of social equity and public health planning. In urban environments like Chicago, unequal distribution of health services often reflects systemic social and racial inequities. The southern region of Chicago has long been recognized for having healthcare disparities, shaped by economic instability, historical patterns of segregation, and limited access to quality care. These disparities in geographic access have been shown to worsen chronic disease outcomes, reduce quality of life, and disproportionately affect low-income and marginalized populations (Luo & Wang, 2003; Murad, 2018).

➢ *Objective*

The objective of this project is to evaluate existing disparities in healthcare accessibility within the study area as well as enhance healthcare facility placement through multimodal transportation analysis and location allocation modeling.

The healthcare access disparities are in seven adjoining Southern Chicago neighborhoods, namely, South Shore, Grand Crossing, Chatham, Burnside, Calumet Heights, Jackson Park, and Woodlawn. These contiguous areas were selected based on observed patterns of socio-spatial vulnerability, high population density, and apparent healthcare deficiencies, identified through spatial overlay analysis of low-income census data, population distribution, and hospital locations on the Chicago map. It was discovered that most of the existing healthcare facilities were located within high-income areas. This emphasizes the need for equity in healthcare access, especially for low-income areas.
The project integrates multimodal network analysis and location-allocation modeling to identify service gaps and recommend spatially optimized facility placements. Special attention is given to equity by integrating normalized demographic metrics and walking access, ensuring the proposed solutions address both areas of greatest need and real-world feasibility. The resulting findings are intended to support evidence-based decision-making in health infrastructure planning, contributing to broader public health goals of fairness and accessibility.

➢ *Study Area and Data Sources*

The study area is approximately 11,962 acres across the seven contiguous neighborhoods in Southern Chicago. To define a unified spatial extent for analysis, the boundaries of the seven neighborhoods were dissolved into a single polygon feature, forming a single boundary. Three primary datasets were integrated for spatial analysis: (1) road networks and footpaths are obtained from OpenStreetMap via Geofabrik in shapefile format, (2) healthcare facility locations were sourced from the ArcGIS Living Atlas (uploaded by United States Emergency Services, Federal Data), also in shapefile format, and (3) demographic data, including low-income census tracts and population density, retrieved from the U.S. Census Bureau and City of Chicago data portals in geodatabase format respectively. These datasets provided the necessary spatial layers for evaluating multimodal healthcare accessibility, identifying underserved areas, and informing location-allocation modeling.

Below are maps showing the location of the Study Area (*Figure 1*) and Healthcare Facility Locations and their locations on the low-income census tract (*Figure 2*).

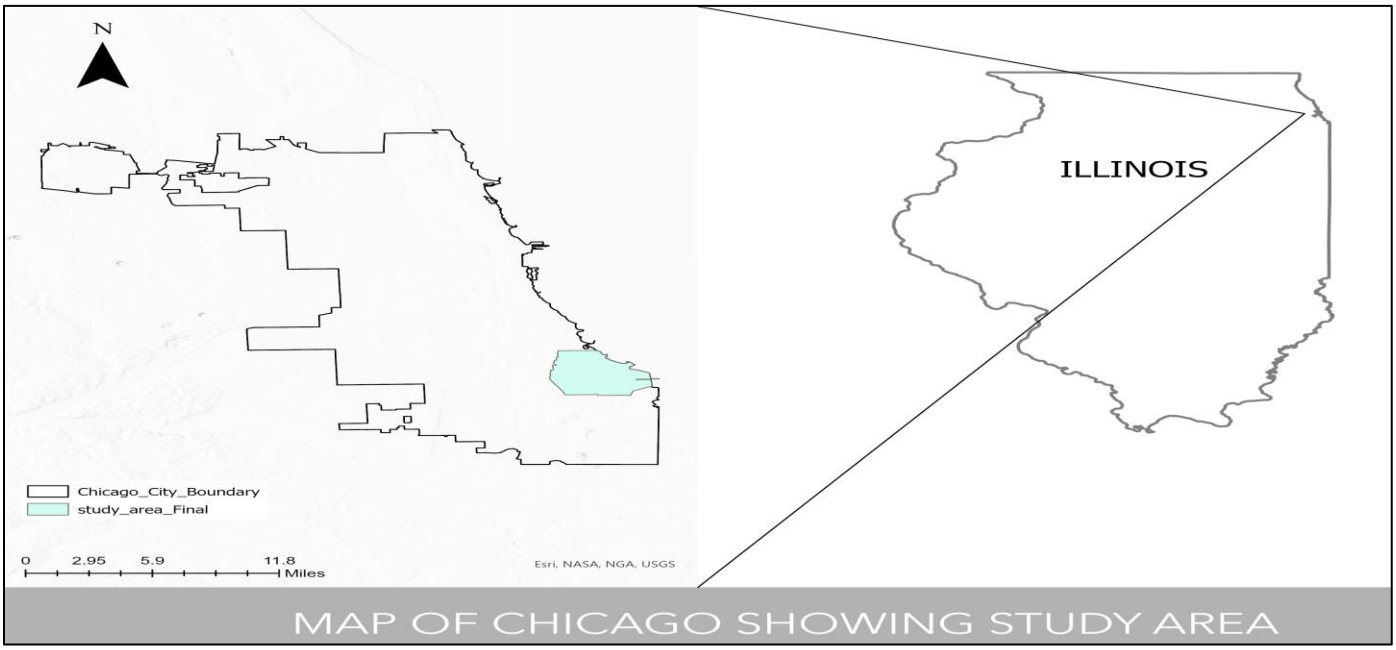

Fig 1 Study Area

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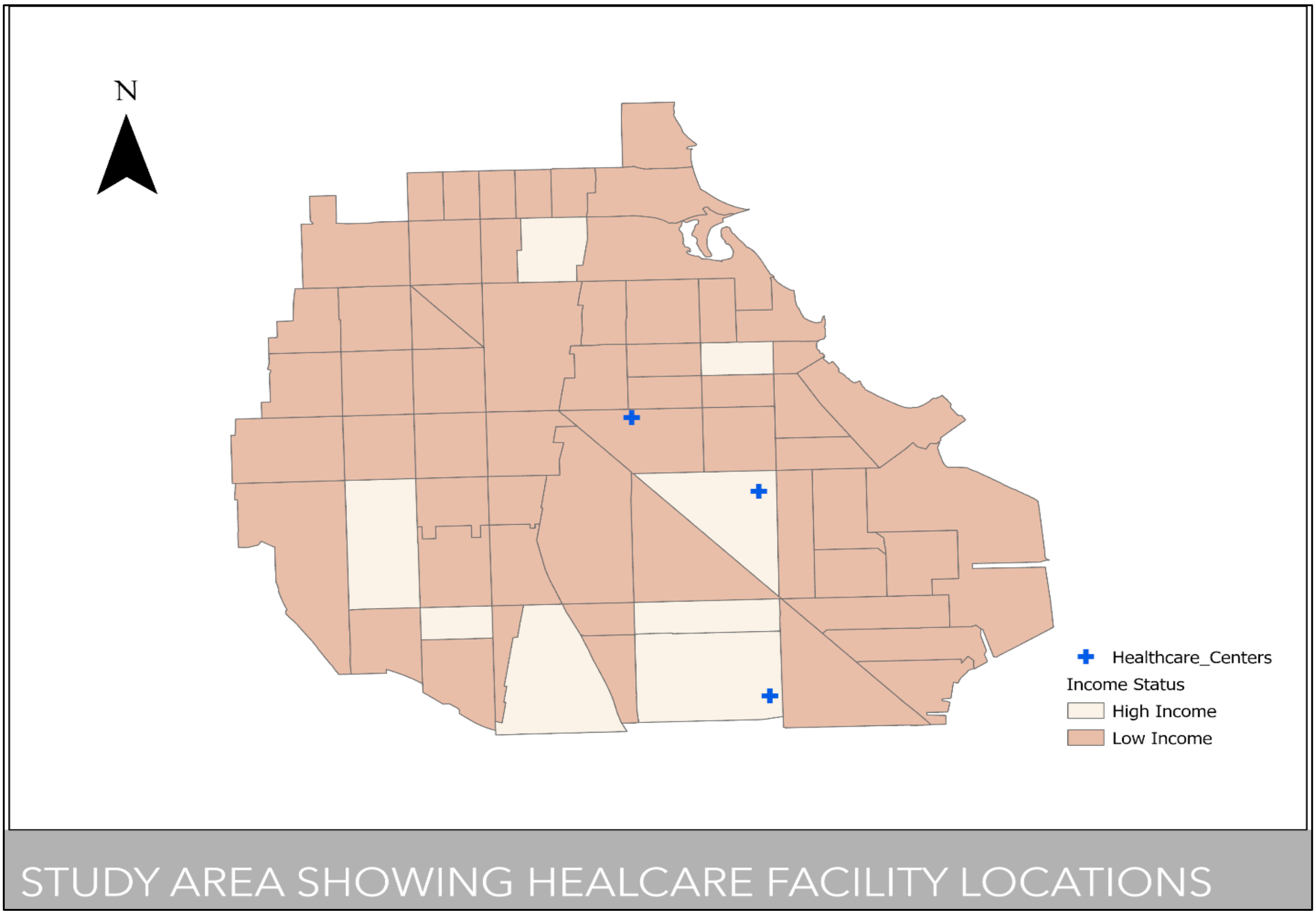

Fig 2 Healthcare Facility Locations

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CHAPTER TWO
METHODOLOGY

➢ *Network Dataset Development*

A multimodal network dataset was developed by merging roads and footpaths into a single system representing both driving and walking conditions. Road features were classified based on access type, with car-accessible roads and pedestrian-only paths separated using attribute data from OpenStreetMap sources. Travel speeds were assigned by mode: existing speed limits from the OSM data for driving and a standard 5 km/h for walking. The walking speed used in this project is in line with standard assumptions used in transportation planning and public health accessibility studies (World Health Organization, 2010; Transport Research Board, 2013). Restrictions were applied to prevent pedestrians from using highways, vehicles from using footpaths, and to enforce one-way travel where applicable. The network was carefully checked to ensure all segments connected logically and realistically, providing a reliable foundation for travel-time and accessibility modeling.

The inclusion of walking is crucial for low-income neighborhoods, where vehicle ownership is lower and public transit access is irregular. Studies in Jeddah and Riyadh also highlight the critical role of walking-based accessibility in healthcare planning, particularly for vulnerable urban populations (Mansour, 2016; Murad, 2018).

➢ *Demand Point Preparation*

Demand points were created by creating the centroids from the census tracts within the study area, thereby establishing a spatial framework for modeling healthcare needs. Each centroid is characterized by key demographic attributes, including total population, percentage of households below the poverty line, median household income, and ultimately, Low-Income status categorized under (Qualified/Not Qualified). A binary low-income status indicator was also assigned, coded as 1 for Qualified and 0 for Not Qualified. Using these attributes, three distinct demand fields were developed to capture different dimensions of healthcare need:

- Population Demand — representing the total number of residents.
- Binary Low-Income Demand — prioritizing tracts where most households are low-income.
- Equity-Based Demand Index — a normalized metric combining population size and low-income status to balance the influence of both vulnerability and scale. This, in other words, can be termed as Amplifying Demand for Low-Income Tracts. The following is the formula applied:

$$EquityDemand = TotalPopulation \times (1 + LowIncomeStatus)$$

Where:

Total Population is the number of residents within each tract.

Low-Income Status is a binary value (1 = low-income tract, 0 = not low-income).

This method effectively doubles the weight of demand for tracts classified as low-income.

Each field captures a unique facet of spatial need. Normalization allowed equity weighting across different data scales, an approach recommended in comparative accessibility studies (Guagliardo, 2004; Luo & Wang, 2003).

Figure 3 below shows thematic maps matched with each scenario's centroids (demand weights) representations. The centroids are represented by graduated symbols.

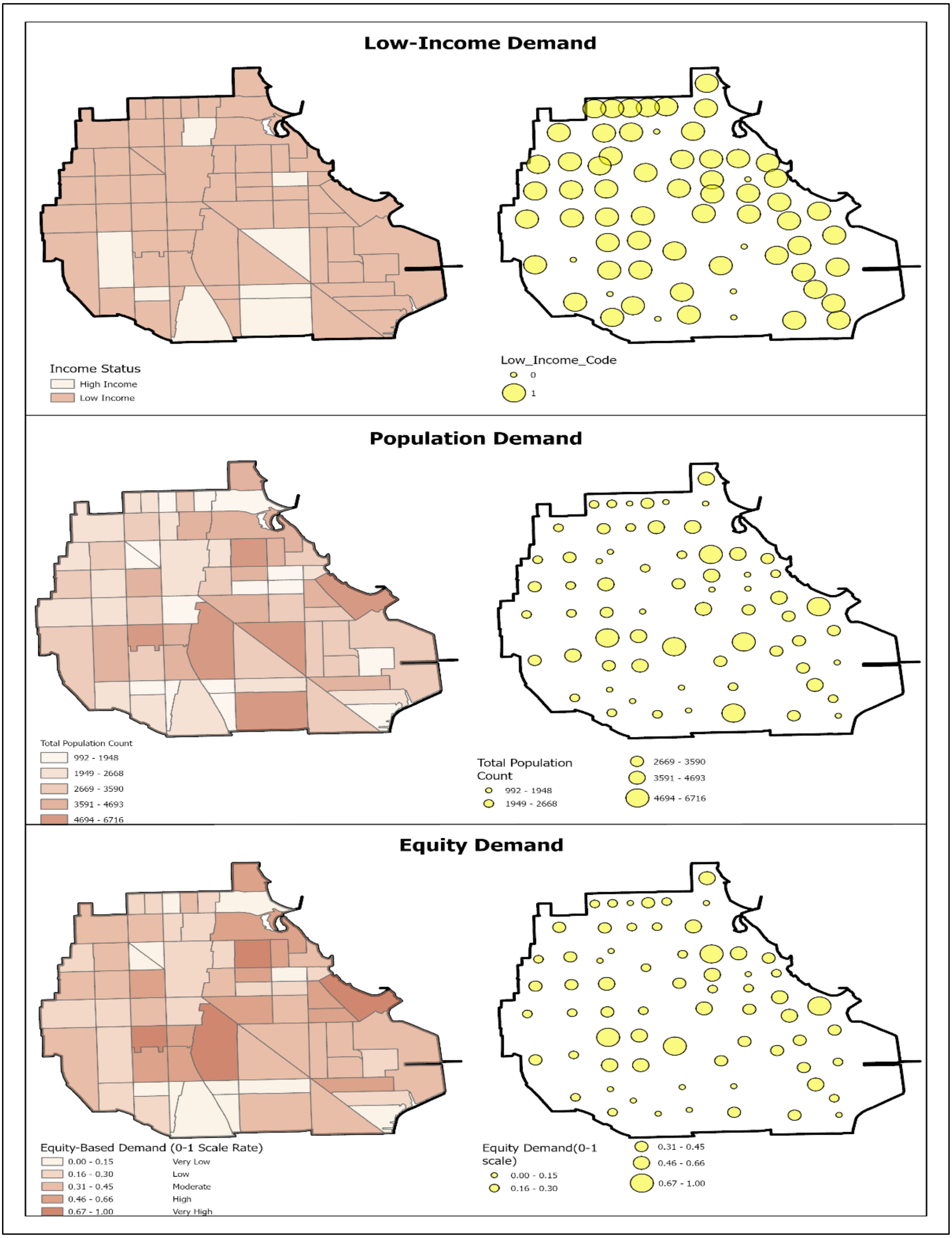

Fig 3 Healthcare Demand Types by Tract and Centroid: Low-Income, Population, and Equity-Based Demand. Left Panels Show Tract Classifications; Right Panels Show Weighted Centroids used for Location-Allocation.

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The left panels of Figure 3 display the census tract classifications for Low-Income Demand, Population Demand, and Equity-Based Demand, based on the underlying attribute data. The right panels visualize the corresponding demand centroids using graduated symbols to represent the relative weight of each centroid under each scenario.

In the Low-Income Demand map, centroid sizes are uniform, reflecting the binary classification [qualified (1) vs. not qualified (0)]. In contrast, Population and Equity Demand centroids vary continuously in size, corresponding to normalized values representing total population and equity-adjusted need, respectively. For visual interpretation of the map, the population demand is represented with actual population count in the legend, however, the normalized (0-1) scale centroids were used as weights for the location allocation modeling to ensure a balanced demand input for all scenarios. These demand centroids as demand points and also candidate points/locations provided a vital foundation for accurately modeling healthcare accessibility and optimizing facility placement in subsequent analyses.

- *Normalizing Demand Values*

To ensure comparability across tracts, both the equity-based demand values and the raw total population values were normalized on a common scale. Normalization was performed using the following formula:

$$Normalized\ Value = \ (\mathcal{X} - \min(\mathcal{X}))/(\max(\mathcal{X}) - \min(\mathcal{X}))$$

Where $\mathcal{X}$ represents either the Equity Demand or the Total Population value for a tract.

Here, min $(\mathcal{X})$ and max $(\mathcal{X})$ represent the minimum and maximum observed values across all tracts. This scaling method transforms all values between 0 and 1, allowing different demand types to be compared fairly and integrated into subsequent location-allocation modeling.

➢ *Service Area Analysis*

Service areas were generated using continuous travel-time thresholds of 5, 10, and 15 minutes for both walking and driving modes. These thresholds represent immediate, convenient, and acceptable travel distances for healthcare access, respectively, which are consistent with public health standards recommended by the World Health Organization and the Centers for Disease Control (CDC). Walking accessibility was prioritized, given its critical relevance to low-income urban populations who often have limited access to private vehicles.

The travel-time polygons were overlaid onto the multimodal network and hollow census tracts to visually assess coverage gaps across the study area, as shown in *Figure 4.* Areas lying beyond the 15-minute threshold for walking or driving were classified as underserved zones. Analysis of existing healthcare facilities showed that many high-demand census tracts fell outside of walking service areas, revealing significant spatial disparities in healthcare access. Meanwhile, driving service areas achieved near-complete coverage of the entire study area, although this is likely to exaggerate real-world accessibility, where there are obvious socio-economic disparities in car ownership across the study area, particularly among low-income non-driving populations. This is because low-income populations are less likely to own private vehicles, resulting in higher dependency on walking.

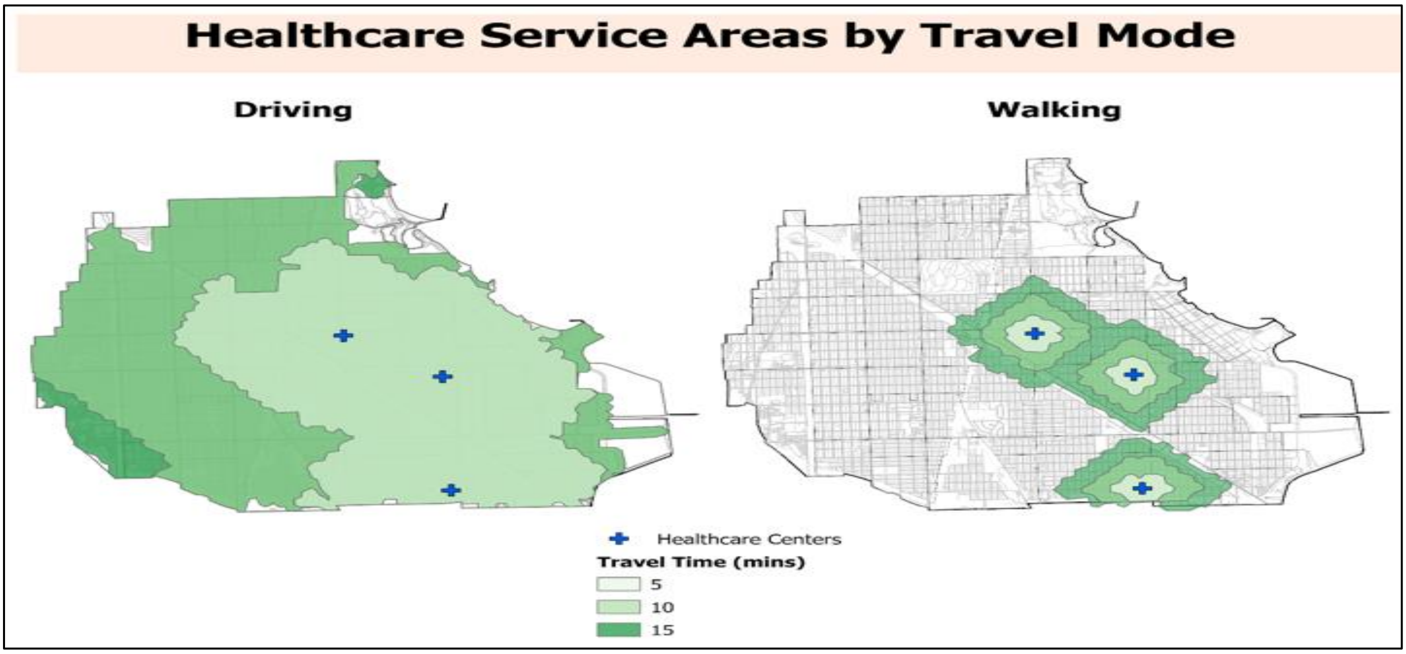

Fig 4 Healthcare Service Areas by Travel Mode in the Study Area, Subsection of Southern Chicago.

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The map shows a strong contrast between driving and walking healthcare accessibility. Driving service areas (left panel) cover almost the entire study area within 15 minutes, suggesting strong potential accessibility for car owners. In contrast, walking service areas (right panel) are limited to small zones around existing healthcare centers, highlighting substantial barriers for residents without private vehicles. These disparities illustrate the vital need to prioritize walking access improvements in urban healthcare planning.

- *Location-Allocation Modeling*

Location-allocation modeling was performed to determine the optimal siting of new healthcare facilities under the three distinct demand scenarios. The "Minimize Impedance" (P-Median) strategy was used, aiming to reduce total weighted travel distance and time, a widely recognized proxy for service efficiency (Wang & Luo, 2005). The mathematical objective of the model was to minimize the sum of weighted travel times across all demand points, expressed as:

$$Minimize = \sum(\text{Travel Time } \times \text{Demand})$$

The model identified the nearest facility for each demand location, multiplied the travel time by the demand weight (population or equity-adjusted value), and aggregated these across the network. New facility locations that minimize the total travel burden were then selected by the model.

The modeling process incorporated both existing and candidate facilities. The three existing healthcare facilities were included as required facilities to reflect real-world service continuity, while 69 candidate sites, the centroids, were included. The centroids were then again input to the model as demand weights to evaluate for new healthcare placements. An equal number of 10 new facilities was assigned across all demand scenarios to ensure consistent analytical comparison between models. Additionally, a 15-minute walking threshold was applied based on public health and urban planning standards , reflecting an inclusive benchmark for essential service accessibility, particularly for non-driving populations.

Three models were executed to reflect different access priorities: binary low-income demand, normalized total population demand, and normalized equity-based demand. Each model produced optimized facility locations and allocation lines linking demand points to their assigned facilities, thereby capturing variations in spatial accessibility under different weighting strategies. The total weighted demand captured by each new facility was then summarized to inform comparative analysis and ranking.

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CHAPTER FOUR
FACILITY RANKING AND LABELING

Once the location-allocation models have been run, the newly sited facilities were evaluated by aggregating the total weighted demand they served. This was done through field joins and demand summarizations between allocation lines and demand points. The facilities were ordered in descending order based on the total weighted demand scores they achieved, with the facility achieving the highest score assigned Rank 1. This demand-driven ranking approach provided a consistent and objective basis for comparing the spatial effectiveness of facility placements across the three scenarios, independent of arbitrary assignment.

Each optimized facility was labeled with its corresponding rank on the final map as (1,2,3,…). This enables a clear visual interpretation of the outputs. Although existing healthcare facilities were included in the optimization model as required facilities, they were excluded from the ranking analysis to maintain the integrity of the comparative evaluation. Involving existing healthcare facilities in the ranking process would have introduced biases based on pre-existing accessibility patterns, thereby undermining the goal of objectively assessing newly optimized solutions. This methodological choice aligns with best practices in spatial allocation modeling (Luo & Whippo, 2012), ensuring that rankings accurately reflect the contribution of newly selected sites to improving healthcare accessibility and equity.

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CHAPTER FIVE
RESULTS AND DISCUSSION

Each demand scenario produced distinct patterns of newly sited facility locations, reflecting the priorities embedded in the demand weighting strategies.

The Low-Income Demand scenario produced a more equitable spatial spread of new facilities across the study area. Sited predominantly within or adjacent to low-income tracts, the new locations expanded coverage into underserved low-income areas. This distribution aligned more closely with public health equity goals by prioritizing service to low-income, vulnerable areas.

In the Population Demand scenario, the optimized facilities were concentrated in areas of higher total population density. This configuration captured a substantial portion of the overall population without considering whether it was a low-income area or not.

The Equity-Based Demand scenario yielded the most balanced distribution of newly sited facilities, integrating both population density and socioeconomic need. Facilities were strategically positioned to serve low-income areas that are highly populated, demonstrating an allocation pattern that maximized both service efficiency and social equity.

In all, the placement of newly optimized facilities highlights the trade-offs between maximizing total service reach and promoting equitable access. The results illustrate that while purely population-based models favor efficiency, equity-weighted approaches provide more inclusive and socially responsive spatial solutions without entirely sacrificing operational effectiveness.

The map in *Figure 5* below displays the top-ranked facility locations generated under each demand-weighted scenario: Low-Income, Population, and Equity. New facilities are labeled numerically (1, 2, 3, …) in order of performance rank within that scenario, while existing facilities are shown but unlabeled to reduce visual clutter, and since they were not ranked. A comparative summary of rankings across all scenarios is provided in *Table 1* below.

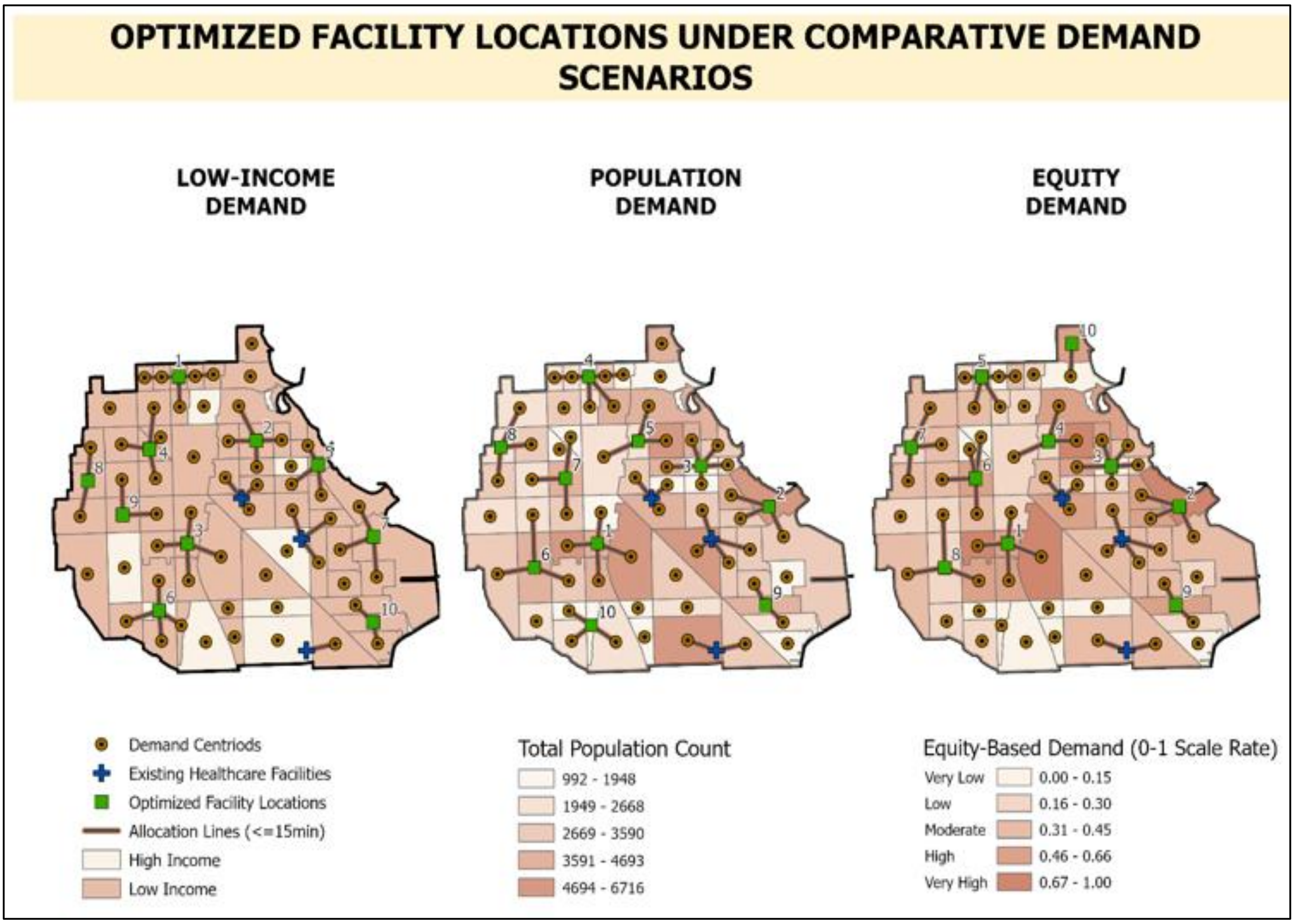

Fig 5 Optimized Healthcare Facility Locations for Low-Income, Population, and Equity Demand Models. Facilities are Ranked Based on Cumulative Demand Capture, with allocation lines Indicating Service Assignment within a 15-Minute Travel Time

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New Facility Cumulative Demand Scores and Rankings Across Low-Income, Population, and Equity-Based Demand Scenarios.

Table 1 Cumulative Demand Scores and Corresponding Facility Rankings Under Low-Income, Population, and Equity-Based Demand Scenarios. Higher Scores Indicate a Greater Contribution to Total Demand Coverage.

New Facility Rank	Low-Income Demand (Weighted Score)	Population Demand (Weighted Score)	Equity Demand (Weighted Score)
1	6.00	2.79	2.88
2	5.00	2.36	2.43
3	5.00	1.93	1.96
4	5.00	1.75	1.80
5	4.00	1.70	1.66
6	4.00	1.69	1.51
7	4.00	1.36	1.39
8	3.00	1.28	1.39
9	3.00	1.05	1.13
10	3.00	0.72	0.68

For the Low-Income Demand Scenario, demand scores represent the number of low-income demand centroids captured. Since a binary variable, [low-income (1) vs. not low-income (0)] was used, each facility's score indicates the extent to which it expanded access for low-income areas.

➢ *Comparative Analysis of Ranks Across the Scenarios*

A detailed examination of cumulative demand scores and facility ranks across the three modeled scenarios — Low-Income Demand, Population Demand, and Equity-Based Demand — reveals how different definitions of need substantially influence the performance value of optimized facility locations. This comparative analysis goes beyond spatial placement to explore shifts in facility importance across different planning priorities.

In the Low-Income Demand scenario, facilities were ranked according to their ability to capture the greatest number of low-income demand points. Facilities that achieved the highest ranks were those strategically located within or adjacent to vulnerable tracts with high proportions of low-income households. The ranking behavior in this model exhibited a relatively gradual decline in cumulative scores across facilities, indicating a more even spread of social vulnerability throughout the study area (reference, *Table 1*). Facilities that ranked highly under this scenario often performed less prominently in the Population Demand model, for example, rank 1 in the low-income scenario is rank 4 in the population demand scenario. This demonstrates that locations critical for serving socioeconomically disadvantaged groups are not necessarily those that serve the largest number of people. This shift in facility importance highlights the necessity of explicitly weighting equity in healthcare planning to ensure service expansion reaches the highest demand, vulnerable populations.

In the Population Demand scenario, the ranking pattern was more sharply hierarchical. The top-ranked facilities captured large portions of the total population quickly, particularly from densely populated zones. After the sixth-ranked facility, however, the incremental contribution to total demand declined steeply. This sharp drop-off reflects saturation of easily accessible, high-population tracts early in the allocation process. Facilities that performed highly in the Low-Income Demand model often ranked lower here, because their service areas are characterized by smaller population counts, despite being qualified as low-income. This divergence illustrates that models that are focused purely on total numbers can reinforce existing geographic inequalities by favoring already advantaged regions with higher residential densities.

The Equity-Based Demand scenario produced a blended ranking behavior, combining elements of both previous models. Facilities that captured both large population counts and significantly low-income demand tended to rise to the top higher ranks. On the contrary, facilities highly specialized for only one dimension, meaning, it is either serving many people or primarily serving vulnerable groups, ranked lower under the integrated equity approach. A typical example is the facility ranked sixth in the Population demand scenario, which is one dimension - High Income, ranked eighth in the Equity demand scenario. This balancing of service efficiency and social fairness demonstrates the strength of equity-weighted modeling in healthcare planning. Facilities ranked 1 through 5 in this scenario tended to be strategically located at transitional zones — areas where high population density and social vulnerability intersect, ensuring the widest possible benefit with targeted responsiveness to community needs.

Comparing facility ranks across all three scenarios reveals the sensitivity of spatial prioritization to underlying demand assumptions. Looking at both the Population demand scenario and Equity demand Scenario, some facilities remained equally ranked, for example, from Rank 1 through to Rank 3 remained the same for both models. Others also maintained relatively stable, high ranks across all the models, suggesting strong versatility regardless of planning focus. These consistently high-performing facilities are particularly valuable for real-world investment, as they align with both efficiency and equity goals. Conversely, other

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facilities fluctuated significantly in their rank depending on the scenario, highlighting the importance of scenario testing to avoid reinforcing hidden biases in facility placement.

Overall, the comparative ranking analysis demonstrates that while maximizing population coverage may offer immediate efficiency, incorporating low-income and equity-based priorities provides a more socially responsible and sustainable strategy for health infrastructure development. Policymakers seeking to advance healthcare access equity must therefore engage in deliberate scenario planning and adopt multi-criteria evaluation frameworks to ensure that facility siting decisions align not only with operational goals but with broader social justice objectives. Future studies could enhance this approach by incorporating dynamic demand models, seasonal variations in healthcare usage, or weighting factors linked to chronic disease prevalence and health outcomes.

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CHAPTER SIX
CONCLUSION

This project has demonstrated how GIS-based multimodal network and location allocation modeling can effectively uncover, visualize, and address healthcare access disparities in urban environments. By integrating road and pedestrian networks with demographic data, the analysis revealed important spatial patterns of inequity that would be difficult to detect without geographic information systems.

The evaluation of three contrasting demand scenarios — binary low-income status, total population, and equity-based demand — provided valuable insight into how different definitions of need influence facility siting outcomes. Each model highlighted different priorities, showing that reliance solely on population counts may unintentionally reinforce existing inequalities, while incorporating socioeconomic vulnerability leads to more inclusive planning outcomes.

Among the models tested, the equity-based approach delivered the most spatially just results. It successfully balanced the dual goals of maximizing service reach and prioritizing underserved populations, demonstrating that equity-driven healthcare planning is not only ethically essential but also spatially feasible within real-world transportation constraints. This finding reinforces the importance of moving beyond traditional efficiency-based models toward frameworks that explicitly account for social determinants of health and geographic disadvantage.

The methodology applied in this project offers a replicable template for cities seeking to enhance socially responsive infrastructure planning. Policymakers, urban planners, and public health officials can use the ranked facility outputs, service area maps, and demand coverage metrics produced through this analysis to guide investment decisions, prioritize areas of greatest need, and evaluate progress toward more equitable health access over time.

Ultimately, this project underscores the critical role of GIS as a decision-support tool in promoting social justice through urban health infrastructure planning. Future research could extend this work by incorporating additional modes of transportation, real-time population dynamics, and health outcomes data to further refine spatial accessibility models and strengthen policy recommendations.

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