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Beyond the Rankings: A Tract-Level Spatial Accessibility Analysis of Urban Livability in Fargo, North Dakota, United States

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Abstract

Aggregate livability indices consistently rank Fargo, North Dakota, among the most livable small-to-mid-sized U.S. cities, yet city-level scores obscure whether favorable average performance reflects equitable neighborhood-level access to essential amenities. However, evidence on whether favorable citywide livability rankings correspond to equitable neighborhood-level access in small- and mid-sized U.S. cities remains limited. To address this gap, this study conducts a tract-level spatial accessibility analysis in Fargo, examining access to grocery stores, healthcare facilities, and parks across 38 census tracts using road network-based nearest-facility assignment, a Composite Accessibility Index (CAI), and Gini coefficients. Results reveal that despite strong aggregate rankings, approximately 9700 residents (8.0% of the study-area population of 121,219) reside in the bottom composite accessibility quartile. Standard Gini coefficients ranged from 0.081 to 0.093, while population-weighted Gini coefficients were lower (grocery = 0.040; healthcare = 0.042; parks = 0.029; CAI = 0.029), indicating modest citywide inequality. Nevertheless, the worst-served peripheral tract recorded a CAI of 0, with network distances ranging from 6.9 to 7.8 miles across the three amenity types. A sensitivity analysis confirms robustness across threshold choices. These findings indicate that modest citywide inequality can coexist with localized accessibility disadvantages in peripheral tracts, supporting spatially disaggregated, equity-oriented livability assessment.

Keywords: spatial accessibility; urban livability; Gini coefficient; census tract; nearest-facility analysis; composite accessibility index; Fargo; mid-sized cities; neighborhood inequality



Academic Editor: Xing Gao

Received: 30 July 2026

Revised: 8 September 2026

Accepted: 11 September 2026

Published: 13 September 2026

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1. Introduction

Cities around the world are increasingly evaluated through the lens of livability, a multidimensional concept that encompasses the quality of the urban environment, the availability of essential services, and the overall wellbeing of residents [1]. Over the past two decades, a proliferation of aggregate livability indices produced by organizations such as the Economist Intelligence Unit, Mercer, and various academic and commercial platforms have made city-level rankings a prominent feature of urban policy discourse, real estate decision-making, and civic identity [1,2]. These rankings provide comparable snapshots of urban performance and have shaped how residents, policymakers, investors, and prospective migrants perceive cities.

Fargo, North Dakota exemplifies the kind of mid-sized American city that performs well on aggregate livability measures. North Dakota consistently ranks among the most livable and affordable states in the United States [3]. Fargo has appeared on multiple small-city livability assessments as a regional hub with strong employment, healthcare infrastructure, and quality of life indicators [4]. The American Association of Retired Persons (AARP) Livability Index (2025) assigns Fargo an overall score in the top half of U.S. communities [5], while Livability.com (2026) assigns the city a LivScore of 716 out of 1000, ranking it highest for housing, education, and transportation [6]. AreaVibes (2025) assigns Fargo an exceptional livability score of 85 out of 100, ranking it first among all North Dakota cities and better than 97% of U.S. communities, substantially above both the North Dakota state average (62) and the national average (63) [7]. As the most populous city in North Dakota and the economic and cultural center of the Fargo-Moorhead metropolitan area, Fargo's favorable aggregate rankings reflect real strengths: a diversified economy anchored by healthcare and higher education, consistently low unemployment, and a growing population that has nearly tripled since 1980. For a city of its size, Fargo's aggregate performance on standard livability measures is genuinely impressive. Yet aggregate livability rankings, by design, produce a single summary score for an entire city [8], a statistical artifact that obscures the spatial variation in conditions experienced by residents across different neighborhoods. Notably, the AARP Livability Index (2025) itself reveals zip code scores within Fargo ranging from 23 to 75 out of 100, a within-city range of 52 points, suggesting that even within a high-performing city, meaningful neighborhood-level differences in livability conditions exist [5]. A city's average accessibility to grocery stores, healthcare, and parks tells us nothing about which neighborhoods are closer to these amenities, and which are farther away, or whether that proximity is evenly distributed across the city's census tracts. Urban scholarship increasingly asks, 'Livability for whom?' because citywide aggregate indices can obscure important variations in livability across neighborhoods and population groups [9]. As cities grow and their populations diversify, the gap between aggregate performance and neighborhood-level reality may widen in ways that standard ranking systems fail to detect [10,11].

This concern is particularly salient for small and mid-sized American cities like Fargo. The urban livability literature has disproportionately focused on large metropolitan areas and cities in East Asia and Europe, leaving the neighborhood-level dynamics of smaller regional hubs largely unstudied [12]. When Fargo performs well on national livability indices, it is rarely clear whether that performance reflects evenly distributed access across the city's neighborhoods. Citywide accessibility summaries can conceal neighborhood-level disparities, an instance of the aggregation bias documented in the statistical literature as Simpson's Paradox [13]. Evidence from North American cities shows that relatively favorable overall accessibility can coexist with poorer access to essential amenities among socioeconomically disadvantaged communities [11].

This study addresses these gaps by conducting a tract-level spatial accessibility analysis of urban livability in Fargo, North Dakota (The Scopus and Web of Science searches described in Section 2.1 did not identify a directly comparable tract-level study of Fargo. However, because database coverage, indexing, and terminology may omit relevant research, the absence of an identified study cannot establish historical priority. Accordingly, this study does not make a categorical claim of being the first analysis of its kind). Using road network-based nearest-facility shortest-path analysis applied to three core amenity categories—grocery stores, healthcare facilities, and parks across all 38 census tracts in the city, the study constructs normalized accessibility scores, a Composite Accessibility Index (CAI), and Gini coefficients of accessibility inequality for each amenity type and for the composite measure. Population-weighted Gini coefficients also quantify the share of

Fargo's residents experiencing the lowest levels of amenity access. The tract-level findings are interpreted alongside Fargo's favorable citywide livability rankings to examine how aggregate urban strengths coexist with neighborhood-level differences in amenity access. The analysis provides complementary spatial evidence rather than testing the validity of these broader rankings.

The study is guided by three research questions. First, how does spatial accessibility to grocery stores, healthcare facilities, and parks vary across Fargo's 38 census tracts? Second, how unequal is the distribution of accessibility across tracts, as measured by the Gini coefficient, and how many residents live in the least accessible areas of the city? Third, what additional information about neighborhood-level amenity access do tract-level accessibility measures provide alongside Fargo's favorable citywide livability rankings?

The remainder of this paper is structured as follows. Section 2 presents a systematic literature review organized around four themes identified through keyword co-occurrence analysis: livability index construction and measurement, spatial accessibility and urban amenities, urban livability frameworks and planning, and neighborhood inequality and spatial disparities. Section 3 describes the study area and data sources. Section 4 presents the methodology, including road network-based nearest-facility assignment, normalization procedure, composite index construction, and Gini coefficient computation. Section 5 reports the empirical results for each amenity category and for the composite index. Section 6 discusses the findings in the context of the existing literature and their implications for urban planning and livability measurement. Section 7 concludes with a summary of contributions and directions for future research.

2. Literature Review

2.1. Review Methodology

This review was conducted systematically to identify, map, and synthesize the existing scholarship on urban livability measurement, spatial accessibility, and neighborhood-level inequality. The literature was retrieved from four databases: Scopus, Web of Science, Science Direct, and Google Scholar (via Publish or Perish) [14], using the primary search string:

("livability index" OR "quality of life index" OR "urban livability") AND (city OR cities OR urban) AND (measurement OR assessment OR indicator OR ranking)

Searches were conducted in May 2026, with results restricted to English-language peer-reviewed journal articles published between 2010 and 2026. The initial search returned 2174 records across all databases (Scopus = 500, Web of Science = 530, Science Direct = 149, Google Scholar = 995). Following deduplication using DOI and title matching, 670 unique records remained. All 670 records underwent abstract screening against predetermined inclusion criteria: the paper must (1) address urban or city contexts, (2) directly engage with livability measurement, accessibility assessment, or spatial inequality, and (3) employ empirical or methodological approaches. Medical, clinical, and purely ecological studies were excluded. Following screening, 159 records were retained for thematic analysis. The screening and deduplication process is documented in accordance with the PRISMA guideline [15]. The study-selection process, including the records removed and the criteria used to exclude 511 records during title and abstract screening, is summarized in Appendix A (Figure A1).

To identify thematic structures within the retained literature, keyword co-occurrence analysis was performed using VOSviewer (version 1.6.20) [16,17], based on author keywords from the 159 retained records. A thesaurus file excluded the study's search terms as stop words to prevent them from dominating the network. Threshold sensitivity testing supported an exploratory minimum occurrence threshold of 15, which produced 33 items

in four clusters, with 465 links and a total link strength of 5678 (Table 1, Figure 1). Since formal cluster-validation statistics were not calculated, the resulting thematic structure is interpreted as exploratory.

Table 1. Sensitivity Analysis of VOSviewer Co-occurrence Threshold. TLS = Total Link Strength.

Threshold	Items	Clusters	Links	TLS	Cluster Interpretability
5	184	7	3904	17,342	Low—fragmented, overlapping clusters
10	64	6	1402	14,709	Moderate—some cluster overlap
15 (selected)	33	4	465	5678	High—distinct and coherent clusters
20	18	3	142	4210	Low—overly sparse, themes collapsed

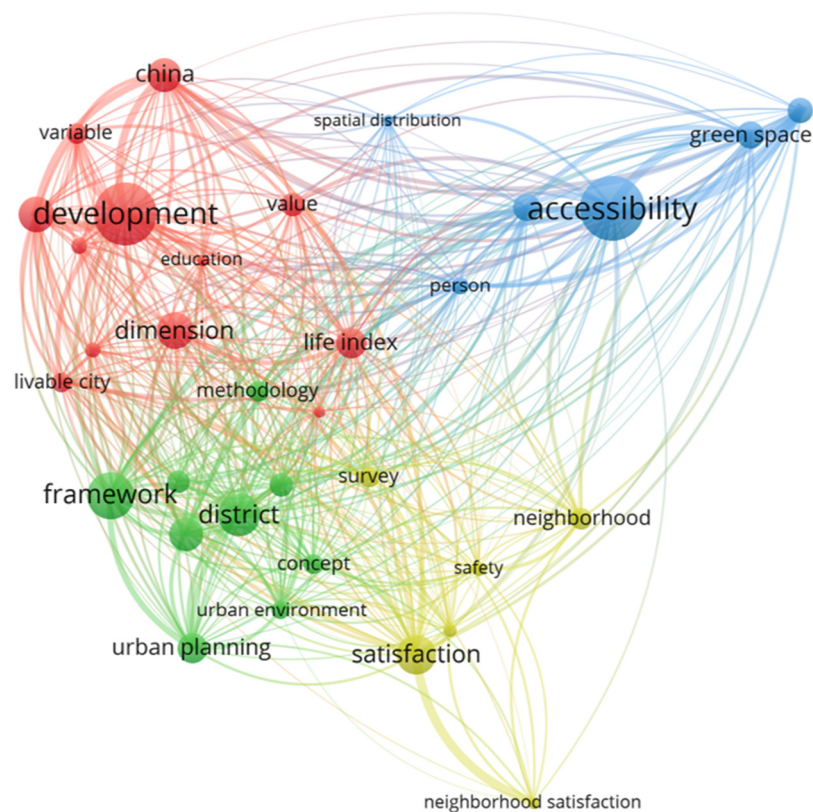


Figure 1. Keyword co-occurrence network of 159 screened records (VOSviewer; minimum threshold = 15; 33 items; 4 clusters; 465 links). Node size reflects keyword frequency; colors represent thematic clusters. Source: Authors’ analysis.

A threshold of 15 was used for exploratory thematic mapping, yielding 33 items in four clusters, with 465 links and a total link strength of 5678 (Figure 1). The threshold represented a pragmatic choice for thematic interpretation rather than a statistically validated optimum. Formal cluster-validation statistics were not calculated, and the resulting thematic structure should therefore be interpreted as exploratory.

The resulting network revealed four thematic clusters that align directly with the conceptual structure of this review: (1) livability index construction and measurement, anchored by the keywords development, dimension, and life index; (2) spatial accessibility and urban amenities, anchored by accessibility and green space; (3) urban livability frameworks and planning, anchored by framework, district, and urban planning; and (4) neighborhood satisfaction and spatial inequality, anchored by satisfaction, neighborhood, and neighborhood satisfaction. These four clusters serve as the organizing framework for the thematic synthesis presented in Section 2.2.

2.2. Thematic Clusters

2.2.1. Theme 1: Livability Measurement and Index Construction

The red cluster in Figure 1, anchored by “development,” “dimension,” and “life index,” concerns the definition, construction, and validation of livability and quality-of-life indices. Although urban livability is central to planning and policy, its measurement remains contested. Early frameworks combined objective socioeconomic and environmental indicators into city-level indices for ranking and comparison [18,19]. Prominent examples include the Economist Intelligence Unit’s Global Liveability Index, Mercer’s Quality of Living Survey, and the CoworkingCafe small-city rankings [20].

However, a growing body of scholarship has questioned the methodological foundations and practical utility of aggregate livability indices. Critics argue that city-level averages conceal substantial intra-urban variation, masking neighborhoods where residents experience conditions far below or above the city mean [21,22]. The question of livability for whom has become increasingly central to this debate, with researchers demonstrating that infrastructural preferences embedded in popular indices systematically favor certain populations while rendering others invisible [21]. This critique is particularly salient for small and mid-sized cities, where aggregate rankings may reflect the performance of a compact urban core while peripheral neighborhoods remain underserved.

Methodologically, the construction of composite livability indices has evolved considerably. Early approaches relied on simple weighted averages of socioeconomic indicators, while more recent frameworks have adopted sophisticated aggregation methods including Principal Component Analysis [23,24], Entropy Weight TOPSIS [25], and Analytic Hierarchy Process [26]. These methodological advances have improved the robustness of composite indices, yet most continue to operate on the city or regional scale, leaving the neighborhood level largely unexamined.

2.2.2. Theme 2: Spatial Accessibility Measurement and Methods

The blue cluster in Figure 1, anchored by “accessibility” and “green space,” concerns methods for measuring proximity and network access to urban amenities. Spatial accessibility, the ease with which residents can reach essential services, is an operationally measurable dimension of livability. Existing research has focused particularly on access to food retailers, healthcare facilities, and green spaces [27–29].

Early accessibility research relied on simple distance or travel-time thresholds, classifying areas as served or underserved based on proximity to facilities. More sophisticated approaches subsequently emerged, including the Two-Step Floating Catchment Area (2SFCA) method, which accounts for both service supply and the demand generated by surrounding populations [27,30]. Further refinements have incorporated multimodal transportation networks, real-time navigation data, and distance-decay functions that better reflect how accessibility diminishes with increasing travel time [18]. Point of Interest (POI) data has become a cornerstone of contemporary accessibility research, enabling systematic identification and mapping of amenity locations across urban areas [31,32].

Although 2SFCA, E2SFCA, and gravity-based models provide more detailed measures of accessibility by incorporating service capacity, population demand, catchment thresholds, and distance-decay effects, they require comparable capacity data and empirically supported model parameters [27,29,30]. The present study instead adopts a nearest-facility network-distance approach because its objective is to measure the minimum road distance from each census tract to one facility in each amenity category rather than capacity-adjusted service availability. This approach provides a transparent and comparable measure across grocery stores, healthcare facilities, and parks, for which a common measure of service ca-

capacity is unavailable. However, it does not account for facility capacity, quality, competing demand, or residents' ability to choose among multiple facilities.

A cross-cutting finding in the spatial accessibility literature holds that amenity availability does not guarantee equitable access. Fei et al. (2025) demonstrated across six global cities that increasing the quantity of green space does not reliably reduce spatial inequality in access [33], a finding with direct implications for policy frameworks that measure livability through amenity counts rather than distributional outcomes. This insight motivates the accessibility-based approach adopted in the present study.

2.2.3. Theme 3: Urban Planning Frameworks and Governance

The green cluster in Figure 1, anchored by “framework,” “district,” and “urban planning,” concerns how urban form, planning decisions, and governance shape livability. This literature situates livability within broader debates concerning sustainable urban development, human-centered planning, and the relationship between the built environment and residents' wellbeing [1,34].

A prominent contribution of this literature is the 15-min city concept, which proposes that urban livability can be operationalized through residents' ability to access essential services within a 15-min walk or cycle from home [29,35]. Comparative livability research has demonstrated that frameworks developed in large metropolitan contexts do not transfer seamlessly to smaller urban areas. Small and mid-sized cities face distinct planning challenges, including limited transit infrastructure, lower-density amenity provision, and greater automobile dependence, which require adapted analytical approaches [12,36]. Yet the literature on small city livability remains comparatively thin, with most empirical frameworks developed and validated in large metropolitan contexts.

2.2.4. Theme 4: Neighborhood Inequality and Spatial Justice

The yellow cluster in Figure 1, anchored by “satisfaction,” “neighborhood,” and “neighborhood satisfaction,” examines neighborhood-level disparities and the distributional consequences of spatial accessibility. This literature challenges reliance on city-level averages by demonstrating substantial variation among neighborhoods, often associated with socioeconomic disadvantage and racial or ethnic composition [37,38].

A consistent finding across this literature is the center–periphery pattern in the distribution of livability. Studies conducted in cities ranging from Warsaw to Ningbo to Mexico City have documented higher livability scores in central urban areas, with declining access to services and amenities as distance from the city center increases [35,39]. Environmental justice perspectives have enriched this literature by connecting spatial inequality in livability to broader patterns of socioeconomic and racial disadvantages. Research has consistently demonstrated that low-income neighborhoods and communities of color experience disproportionately lower access to parks, healthcare, and food retail, compounding other dimensions of disadvantage [40,41].

2.3. Research Gap and Study Motivation

The four thematic clusters identified through this review converge on a clear and consequential gap in the existing literature. First, while livability index methodology has advanced considerably, most assessments remain anchored at the city or regional scale, rendering neighborhood-level variation invisible. Second, spatial accessibility research has developed sophisticated methods for measuring amenity access but has concentrated primarily on large metropolitan areas in East Asia and Europe, leaving small and mid-sized American cities largely unstudied. Third, neighborhood inequality research has demonstrated the importance of fine-grained spatial analysis but has rarely connected these findings to the aggregate city rankings that drive public perception and policy.

The broader research question concerns how favorable citywide livability assessments coexist with neighborhood-level differences in access to essential amenities. Fargo provides an illustrative case of a highly ranked small-to-mid-sized U.S. city for examining this question. The analysis complements aggregate livability assessments rather than testing their validity. Fargo is not assumed to be statistically representative of other cities, and wider applicability requires comparative research.

3. Study Area and Data

3.1. Study Area

Fargo, North Dakota, serves as the empirical case study for this research. As the most populous city in North Dakota, Fargo had a population of 125,990 at the 2020 census and an estimated 136,285 residents in 2024 [42], making it a prototypical mid-sized American city. The city covers a total land area of 50.83 square miles (131.66 km²) and sits on the western bank of the Red River of the North, in the flat terrain of the Red River Valley [43].

Fargo serves as the primary cultural, retail, healthcare, educational, and economic hub for southeastern North Dakota and northwestern Minnesota. Its regional significance is reflected in the composition of its largest employers: Sanford Health (9229 employees) and Essentia Health (1946 employees) anchor the city's healthcare sector, while North Dakota State University (2267 employees) anchors its educational identity [44]. The Fargo-Moorhead metropolitan area had a combined population of 261,600 people and is projected to reach approximately 340,000 by 2045 [45].

The city's demographic profile has diversified substantially over the past two decades. The proportion of non-Hispanic White residents declined from 93.4% in 2000 to 77.8% in 2020, while the Black or African American population grew from 1.0% to 8.6% over the same period, attributable in part to refugee resettlement programs. As of the 2022 American Community Survey, the median household income in Fargo was \$64,432, with approximately 13.3% of the population living at or below the federal poverty line. Fargo's spatial structure follows a classic grid pattern, with growth historically concentrated in the south and southwest of the city [45].

Road-network mapping shows a grid-based pattern in Fargo's established central area (see Section 5.2). The map illustrates the city's municipal boundary, census-tract configuration, road-network structure, established urban core, and principal direction of outward growth. The Red River of the North shapes the city's eastern edge, while newer urban development has expanded primarily toward south Fargo [46]. The peripheral portions of the city contain larger census tracts that extend beyond established concentrations of urban services. This center-periphery structure is relevant to the accessibility analysis because outward residential expansion can increase road-network distances when grocery stores, healthcare facilities, and parks do not develop at the same spatial rate. The accessibility results should therefore be interpreted in relation to Fargo's urban form, particularly the contrast between the established central area and the expanding southern periphery.

3.2. Spatial Units of Analysis

Census tract boundaries were obtained from the U.S. Census Bureau's TIGER/Line 2024 dataset in the NAD83 geographic coordinate system (EPSG:4269) [47]. To isolate the analysis to the Fargo municipal area, the full tract dataset was spatially clipped using the official Fargo city limits shapefile, downloaded from the City of Fargo ArcGIS Hub [48]. The resulting subset comprised 38 census tracts covering the full extent of the city. Each census tract polygon was converted to a centroid point serving as the representative population-demand location in the accessibility analysis.

Population data were obtained from the U.S. Census Bureau's ACS 5-Year Estimates (2019–2023; Table B01003) [49] for all census tracts in Cass County and joined to the 38 tracts comprising the Fargo study area using standardized GEOID identifiers, yielding an initial study-area population total of 167,235. A comparison of each tract's clipped land area with its official Census land area revealed that nine tracts had less than 25% of their area within Fargo. The 25% value was used only to flag tracts for which at least three-quarters of the land area fell outside the city; it was not an inclusion or exclusion threshold. All 38 tracts were retained, and each tract's population was adjusted using its exact proportion of land area within Fargo. This first-order areal-interpolation correction produced an adjusted study-area population of 121,219, which was used for all population-weighted analyses.

The land-area-based population adjustment assumes uniform population density within each original census tract. The resulting in-city populations are therefore estimates rather than direct counts of residents within the clipped portions. Geometric centroids were used to provide a consistent, reproducible single-point representation of the clipped tracts for network-distance comparisons across amenity categories. These locations summarize tract geometry rather than the distribution of residents; population-weighted centroids were not used.

3.3. Amenity Data and Road Network Data

The three amenity categories selected for this study—grocery stores, healthcare facilities, and parks—represent the core dimensions of essential urban service provision most consistently identified in the livability and neighborhood wellbeing literature. Access to grocery stores is a fundamental determinant of food security and daily sustenance, with research consistently linking grocery proximity to diet quality and neighborhood deprivation [50–52]. Access to healthcare facilities reflects the availability of preventive and curative medical services that underpin physical health outcomes across the life course, with more disadvantaged neighborhoods consistently experiencing lower geographic access to care [53,54]. Access to parks and green spaces supports physical activity, mental health, and environmental quality, with evidence demonstrating that proximity to parks is associated with reduced depression, lower stress, and improved physical health among urban residents [55–57].

Locations for all three amenity categories, grocery stores, healthcare facilities, and parks, were extracted from OSM on 22 May 2026, using the QuickOSM plugin (version 2.5.3) in QGIS (version 3.34.14-Prizren). For each category, a key-value query was run with the search extent restricted to the Fargo city limits. Resulting point and polygon feature layers were merged into a single dataset; polygon features were converted to centroid points to provide a consistent, single representative location for each facility. Each merged dataset was clipped to the Fargo city boundary and subjected to visual inspection and quality control to identify and remove duplicate representations of the same establishment.

To assess the potential influence of boundary effects on the accessibility analysis, amenity data were extracted within a 10-mile buffer surrounding the Fargo city limits. The buffered map indicated that a limited number of amenities are located outside the Fargo boundary, with the majority concentrated east of the city in the neighboring municipality of Moorhead, Minnesota, and a few isolated facilities in surrounding areas. These external amenities lie outside the administrative jurisdiction of Fargo and are separated by municipal and, in the case of Moorhead, state boundaries. Moreover, no additional grocery stores or healthcare facilities within the buffer met the study's inclusion criteria, indicating that the boundary choice does not affect the nearest-facility assignments for these two categories. For parks, eligible facilities were identified in Moorhead, Minnesota, but the park OD matrix was not rerun with their inclusion. The boundary effect on park accessi-

bility therefore remains untested, and excluding cross-boundary parks may overestimate park travel distances for some eastern Fargo census tracts. Consequently, the Fargo city boundary remains an appropriate spatial extent for evaluating grocery store and healthcare accessibility. For park accessibility, the potential influence of cross-boundary facilities in Moorhead remains unquantified and is acknowledged as a limitation.

Grocery stores were extracted using the key “shop” with the values “supermarket,” “greengrocer,” and “grocery.” Quality control identified and removed nine duplicate polygon-point pairs (four Walmart, three Cash Wise, and two Family Fare locations), yielding 26 unique stores [58].

Healthcare facilities were extracted using the key “amenity” with the values “hospital,” “clinic,” “doctors,” and “pharmacy” combined with OR logic, capturing a broad range of healthcare service providers. The final dataset comprised 26 unique healthcare facilities, including hospitals, medical clinics, physician offices, and pharmacies [59]. Although hospitals, clinics, physician offices, and pharmacies differ substantially in function, patient demand, and operational capacity, they were grouped in this study as a broad category of healthcare-related destinations. The objective was to measure the minimum road-network distance from each census tract to any commonly used healthcare-related service, rather than accessibility to a particular type or level of clinical care. Comparable studies have incorporated multiple healthcare facility and service types within common or composite spatial-accessibility frameworks. For example, Rabiei-Dastjerdi et al. [60] combined accessibility layers for hospitals, clinics, pharmacies, and laboratories. Similarly, Raeesi et al. [61] integrated accessibility to multiple primary and secondary healthcare services into an overall index. Nevertheless, these facilities should not be interpreted as functionally interchangeable. Since comparable information on service capacity, patient volume, and operational scope was unavailable across facility types in Fargo, the resulting indicator represents generalized geographic proximity rather than service-specific, utilization-based, or capacity-adjusted healthcare access. Future research should separately examine primary care, hospital and emergency care, and pharmacy accessibility.

Parks were extracted using the key “leisure” with the value “park.” The resulting dataset consisted primarily of polygon features representing park boundaries, converted to centroids as described above. The final dataset comprised 92 unique park locations, encompassing neighborhood pocket parks, community parks, and larger recreational facilities managed by the Fargo Park District [58].

Amenity locations were subjected to category-specific validation and quality-control procedures. Of the 26 OSM grocery-store records, 24 (92.3%) were matched to the USDA SNAP Retailer Locator, while the remaining two were confirmed through Google Maps. Healthcare facilities and parks were visually inspected in QGIS, checked for consistency with the Fargo city boundary, and examined for duplicate records. These procedures improved the positional and attribute consistency of the datasets but did not establish their completeness or assess facility capacity, service quality, or operational status. Accordingly, the potential for omitted, outdated, or misclassified OSM records is acknowledged as a study limitation.

Consequently, the Fargo city boundary was retained as the predefined spatial extent for evaluating intra-urban accessibility. No additional grocery stores or healthcare facilities within the 10-mile buffer met the study’s inclusion criteria, indicating that nearest-facility assignments for these two categories were unaffected by the boundary choice. The additional eligible amenities consisted of parks in Moorhead, Minnesota. These parks were excluded because they fall outside the study’s municipal scope, and the park OD matrix was not rerun with their inclusion. Excluding cross-boundary parks may therefore overesti-

mate park travel distances for some eastern Fargo census tracts; this potential boundary effect is acknowledged as a study limitation.

The road network used for all network distance calculations was derived from the Highway Performance Monitoring System (HPMS) dataset provided by the U.S. Bureau of Transportation Statistics (BTS) [62]. The statewide North Dakota road network was extracted and subsequently clipped to the Fargo city limits to create the study-area transportation network. To ensure accurate network connectivity, all census tract centroids and amenity locations were snapped to the nearest road segment using the Snap Geometries to Layer tool in QGIS. A snapping tolerance of 10 m was applied to eliminate minor spatial offsets between points and the road network, thereby ensuring that all origins and destinations were properly connected to the transportation network. This preprocessing step enabled the generation of valid shortest-path routes and reliable origin–destination distance calculations for all tract–amenity pairs included in the analysis.

4. Methodology

4.1. Overview

This study employed a four-stage spatial accessibility methodology to assess the distribution of amenity access across Fargo's 38 census tracts and quantify the degree of inequality in that distribution. The four stages are: (1) origin–destination (OD) matrix construction using road network-based nearest-facility assignment; (2) nearest amenity distance extraction for each census tract; (3) normalization and composite accessibility index construction; and (4) Gini coefficient computation to measure the inequality of accessibility distribution across tracts. Each stage was applied consistently across all three amenity categories (grocery stores, healthcare facilities, and parks), enabling direct comparison of accessibility inequality across service types and the construction of a unified composite measure.

4.2. Origin–Destination Matrix and Nearest-Facility Assignment

To quantify network-based accessibility, an OD matrix was generated between amenity locations and census tract centroids using the OD Matrix from Layers as Lines (m: n) tool in QGIS (version 3.34.14-Prizren). Amenity locations served as origin points, while census tract centroids served as destination points. The shortest-path distance criterion was used to compute the minimum travel distance along the road network between each amenity and every tract centroid. Network distance was used to quantify spatial proximity to amenities along the road network. The network dataset used in this study did not contain segment-level speed attributes, and an HPMS-based travel-time analysis was not conducted. Accordingly, the results describe distance-based accessibility rather than experienced travel time. Congestion, intersection delays, and time-of-day variation are not represented; this limitation is acknowledged in Section 6.6.

Accessibility was operationalized by assigning each census tract to its nearest amenity based on shortest road-network distance. Since no capacity or demand constraints were imposed, the nearest amenity was identified directly from the origin–destination matrix. These minimum-distance values formed the basis for the normalized accessibility scores, Gini coefficients, and CAI presented in subsequent sections.

Prior to OD matrix generation, all amenity locations and census tract centroids were snapped to the nearest road segment using the Snap Geometries to Layer tool in QGIS (version 3.34.14-Prizren) to ensure that all origins and destinations were connected to the transportation network. A topology tolerance of 0.00007 degrees was applied uniformly across all three amenity categories during OD matrix construction to maintain network connectivity at road intersections and eliminate routing discontinuities.

4.3. Normalization and Composite Accessibility Index

To facilitate comparisons across amenity types and enable their integration into a unified accessibility measure, the nearest-amenity distances were transformed using an inverted min–max normalization procedure. This transformation standardized accessibility scores to a common scale from 0 to 1, where 0 represents the lowest and 1 the highest level of accessibility. The inversion ensures that shorter travel distances correspond to higher accessibility scores.

A CAI was subsequently developed to capture overall access to essential urban amenities. For each census tract i , the index was calculated as the arithmetic mean of the normalized accessibility scores for grocery stores, healthcare facilities, and parks:

$$CAI_i = \frac{A_i^{grocery} + A_i^{health} + A_i^{park}}{3} \quad (1)$$

where $A_i^{grocery}$, A_i^{health} , and A_i^{park} denote the normalized accessibility scores for grocery stores, healthcare facilities, and parks, respectively, for census tract i . Equal weights (1/3 each) were adopted as a transparent baseline without prioritizing any amenity category. This represents a study-design choice rather than evidence that residents value grocery, healthcare, and park accessibility equally.

This approach is consistent with the broader livability literature, which views access to essential services and public amenities as complementary components of residents' quality of life and neighborhood well-being [1,34,63]. Weighting sensitivity was assessed using five analyst-selected alternative schemes (Appendix A (Table A1)). Spearman rank correlations compared tract rankings with the equal-weight baseline, while bottom-quartile overlap measured how many of the 10 baseline bottom-quartile tracts were retained under each scheme.

4.4. Gini Coefficient of Accessibility

To evaluate the degree of spatial inequality in accessibility across Fargo's census tracts, Gini coefficients were calculated for each accessibility measure, including grocery store, healthcare, and park accessibility, as well as the CAI. The Gini coefficient is a widely used measure of inequality that ranges from 0, indicating perfect equality, to 1, indicating maximum inequality. Lower Gini values, therefore, reflect a more equitable distribution of accessibility across geographic areas.

The standard Gini coefficient was computed using the following discrete formula:

$$G = \frac{2\sum_{i=1}^n i \cdot x_i}{n\sum_{i=1}^n x_i} - \frac{n+1}{n} \quad (2)$$

where x_i denotes the accessibility score at rank position i after the 38 census tracts are sorted in ascending order ($i = 1$ denotes the least-accessible tract), and n is the total number of census tracts ($n = 38$). This formula was implemented using custom Python functions in NumPy 1.26.4.

Since census tracts vary substantially in population size, population-weighted Gini coefficients were also computed to assess the equity of accessibility from a resident-centered perspective. This approach assigns greater influence to tracts with larger populations, thereby reflecting the distribution of accessibility experienced by residents rather than by geographic units alone. The population-weighted Gini was computed by sorting tracts by accessibility score, calculating cumulative population shares and cumulative accessibility shares, and computing the area under the resulting Lorenz curve using the trapezoidal integration method (NumPy trapz function). Nonparametric 95% bootstrap confidence

intervals were calculated using 5000 resamples of census tracts with replacement. For the population-weighted estimates, each tract's accessibility score and corresponding population were resampled together as paired observations.

To complement the numerical inequality measures, Lorenz curves were constructed for each accessibility indicator. These curves depict the cumulative share of accessibility relative to the cumulative share of census tracts or population, providing a graphical representation of accessibility distribution and allowing direct comparison with the line of perfect equality. Together, the Gini coefficients and Lorenz curves provide a comprehensive assessment of spatial equity in access to essential urban amenities across Fargo.

Global Moran's I assessed spatial autocorrelation across 38 tracts using row-standardized Queen-contiguity weights. Two-sided tests used 9999 permutations (seed = 42), based on absolute deviations from $E[I] = -1/(n - 1)$, with Holm adjustment for four comparisons.

4.5. Comparison to Aggregate Livability Rankings

Tract-level accessibility outcomes were interpreted qualitatively alongside Fargo's published citywide livability rankings. These rankings summarize multiple dimensions of urban conditions, whereas this study measures road-network proximity to three amenity categories and its distribution across census tracts. Because the assessments differ in scope and spatial scale, no direct numerical comparison or statistical test of ranking validity was undertaken. Instead, the comparison examined how favorable citywide assessments coexist with localized accessibility differences and how neighborhood-scale evidence can complement the interpretation of urban livability.

4.6. Software and Transferability

All spatial data processing, origin-destination matrix construction, shortest-path analysis, and map production were conducted using QGIS version 3.34.14-Prizren. Statistical analysis, accessibility normalization, CAI construction, Gini coefficient calculations, and Lorenz curve generation were performed in Python 3.12.3 using the Spyder 5.5.1 integrated development environment (IDE). Python analyses used pandas 3.0.2, NumPy 1.26.4, and Matplotlib 3.10.9. The nearest-facility assignment was computed directly from the OD matrix as a row-wise minimum-distance selection. This procedure is mathematically equivalent to solving an unconstrained assignment problem because each origin is assigned independently to the minimum-distance destination. All datasets used in this study are publicly available from the U.S. Census Bureau, OpenStreetMap, the Bureau of Transportation Statistics, and the City of Fargo ArcGIS Hub, enabling replication of the analytical workflow.

5. Results

5.1. Overview

This section presents the tract-level spatial accessibility findings for Fargo's 38 census tracts across the three amenity categories and synthesizes these into a CAI. For each amenity, results are reported as network distance distributions, normalized accessibility scores, and Gini coefficients that measure the inequality of access across tracts. In addition, population-weighted Gini coefficients are reported to account for variation in tract population size.

5.2. Grocery Store Accessibility

The OD matrix analysis yielded 988 OD pairs across 38 census tracts and 26 grocery store locations, using road network-based nearest-facility assignment in which every tract was guaranteed coverage by its nearest store. Network distances to the nearest grocery store ranged from 0.23 miles to 7.77 miles, with a mean of 1.33 miles and a median of

0.94 miles (Figure 2). Figure 3 illustrates the shortest-path road network routes from each tract centroid to its nearest grocery store, confirming the pronounced spatial disparity between centrally located tracts and the peripheral outlier tract in the city's southern sector. The right-skewed distribution indicates that while the majority of tracts are well served, 33 of 38 tracts lie within 2 miles of the nearest store; a small number of peripheral tracts experience substantially longer travel distances. The most isolated tract requires a network distance of 7.77 miles to reach the nearest grocery store, nearly six times the citywide median.

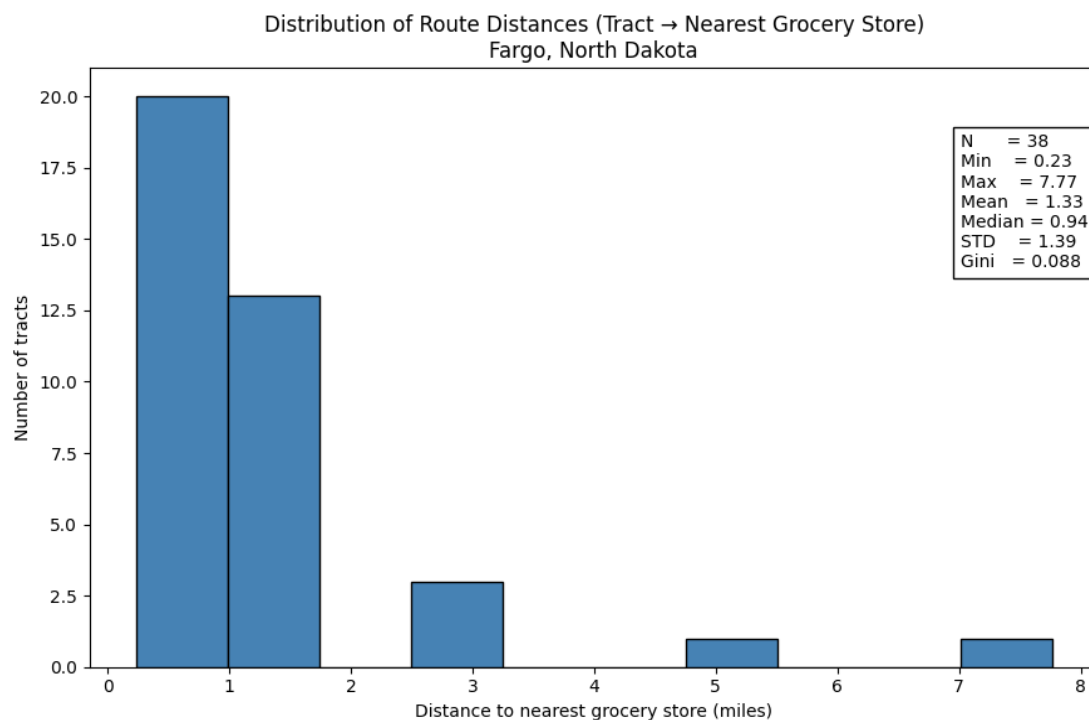


Figure 2. Distribution of road network distances from Fargo census tract centroids to the nearest grocery store ($N = 38$). The right-skewed distribution indicates that most tracts are within 2 miles of a store, while a small number of peripheral tracts experience substantially greater travel distances. Source: Authors' calculations.

Normalized accessibility scores ranged from 0 to 1, with a mean score of 0.854. The standard Gini coefficient for grocery accessibility was 0.088, and the population-weighted Gini was 0.040, both indicating low overall inequality. The bottom quartile of accessibility scores includes 10 census tracts with a combined population of 15,118 residents representing 12.5% of the study-area population, suggesting that despite low aggregate inequality, a substantial share of residents experience meaningfully lower grocery access than the city average.

Figure 4 presents the standard and population-weighted Lorenz curves for grocery accessibility, plotted separately to avoid conflating cumulative shares of tracts and population on a single axis. The standard Lorenz curve (left panel, Gini = 0.088) lies below the line of perfect equality, confirming that grocery access is not evenly distributed across tracts. The population-weighted Lorenz curve (right panel, Gini = 0.040) shows a marginally smaller deviation from the equality line, consistent with the slightly lower population-weighted Gini and indicating that the most poorly served tracts tend to have somewhat smaller populations than the best-served tracts. Both panels nonetheless confirm the presence of meaningful spatial inequality in grocery accessibility that aggregate city-level rankings fail to capture.

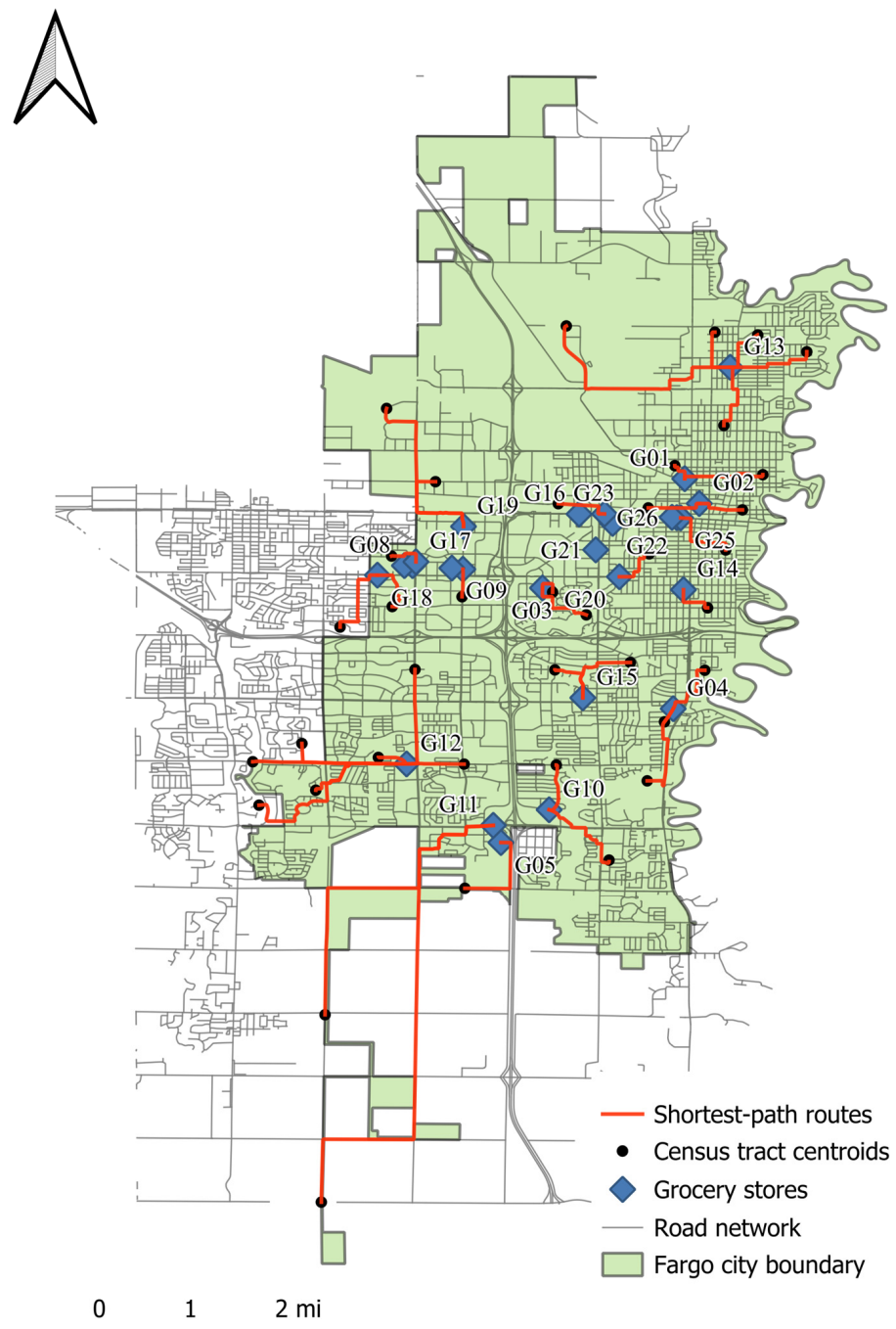


Figure 3. Grocery accessibility in Fargo, North Dakota. Red lines show shortest road-network routes connecting 38 census tract centroids (black dots) to their nearest grocery stores. Blue diamonds indicate the 26 grocery-store locations, identified by G-prefixed labels. Green shading and the outlined boundary denote Fargo’s city limits. Source: Authors’ analysis. Coordinate reference system: NAD83 geographic coordinate system (EPSG:4269). Scale bar in miles. North arrow indicates geographic north.

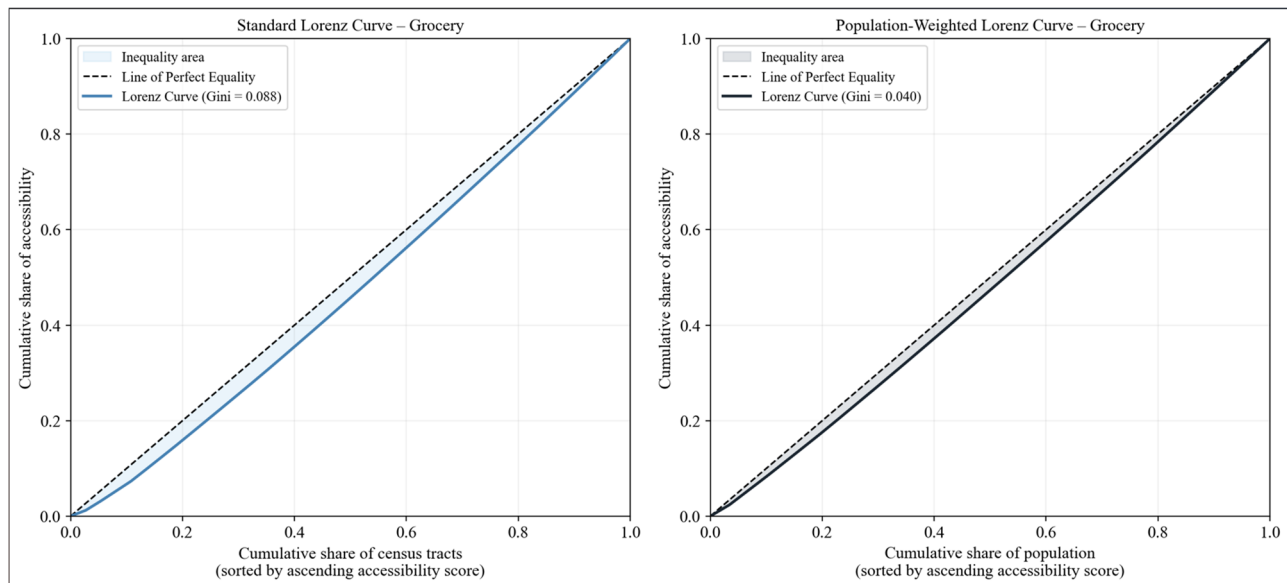


Figure 4. Lorenz curves for grocery store accessibility across Fargo’s 38 census tracts. The standard Lorenz curve ((left) Gini = 0.088) and population-weighted Lorenz curve ((right) Gini = 0.040) both fall below the line of perfect equality, indicating unequal distribution of grocery accessibility across tracts. The slightly lower population-weighted Gini suggests that tracts with poorer accessibility tend to have somewhat smaller populations.

5.3. Healthcare Facility Accessibility

The OD matrix analysis yielded 988 origin-destination pairs across 38 census tracts and 26 healthcare facility locations, using road network-based nearest-facility assignment where every tract was guaranteed coverage by its nearest facility. Network distances to the nearest healthcare facility ranged from 0.15 miles to 7.16 miles, with a mean of 1.33 miles and a median of 1.03 miles (Figure 5). Figure 6 illustrates the shortest-path road network routes from each tract centroid to its nearest healthcare facility, confirming the spatial concentration of healthcare infrastructure in the central and northern portions of the city. The right-skewed distribution indicates that while the majority of tracts are well served, 29 of 38 tracts lie within 2 miles of the nearest facility; a small number of peripheral tracts experience substantially longer travel distances. The most isolated tract requires a network distance of 7.16 miles to reach the nearest healthcare facility, nearly seven times the citywide median.

Normalized accessibility scores ranged from 0 to 1, with a mean score of 0.831, the lowest of the three amenity categories. The standard Gini coefficient for healthcare accessibility was 0.093, and the population-weighted Gini was 0.042, both the highest of the three amenity types. The bottom quartile of accessibility scores included 10 census tracts with a combined population of 13,441 residents, representing 11.1% of the study-area population.

Figure 7 presents the standard and population-weighted Lorenz curves for healthcare accessibility, plotted on separate axes to ensure valid visual comparison. The standard Lorenz curve (left panel, Gini = 0.093) shows the greatest deviation from the line of perfect equality of the three amenity categories, consistent with healthcare exhibiting the highest measured inequality. The population-weighted Lorenz curve (right panel, Gini = 0.042) shows a similarly pronounced deviation, indicating that the concentration of healthcare facilities in central Fargo disadvantages peripheral tracts regardless of their population size.

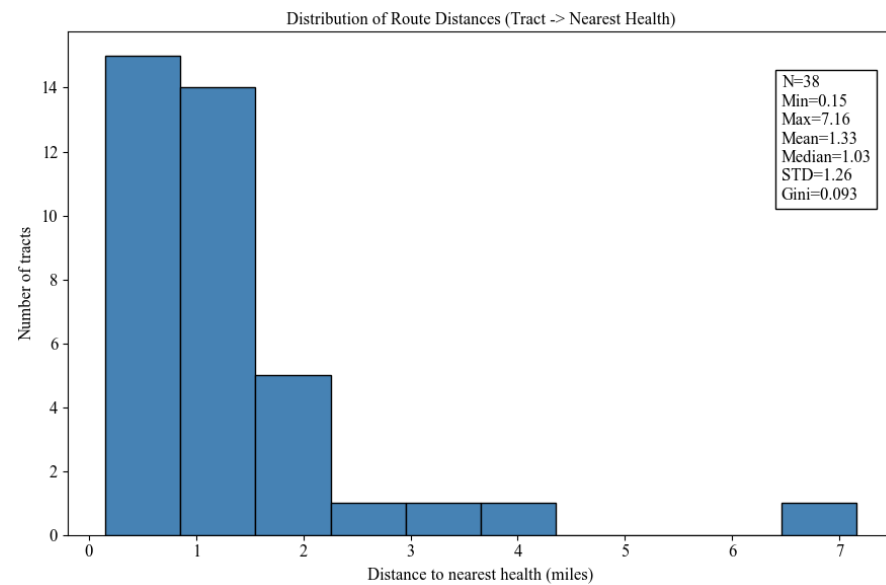


Figure 5. Distribution of road network distances from Fargo census tract centroids to the nearest healthcare facility ($N = 38$). Source: Authors' calculations.

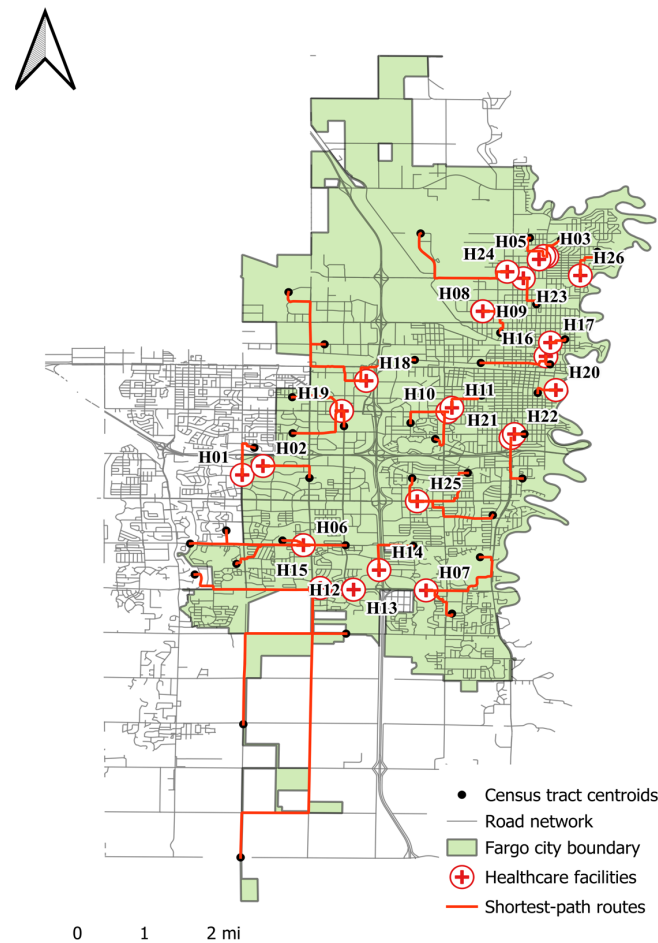


Figure 6. Healthcare accessibility in Fargo, North Dakota. Red lines show the shortest road-network routes connecting 38 census tract centroids (black dots) to their nearest healthcare facilities. Red crosses indicate the 26 facilities, including hospitals, clinics, pharmacies and physician offices, identified by H-prefixed labels. Green shading and the outlined boundary denote Fargo's city limits. Source: Authors' analysis. Coordinate reference system: NAD83 geographic coordinate system (EPSG:4269). Scale bar in miles. North arrow indicates geographic north.

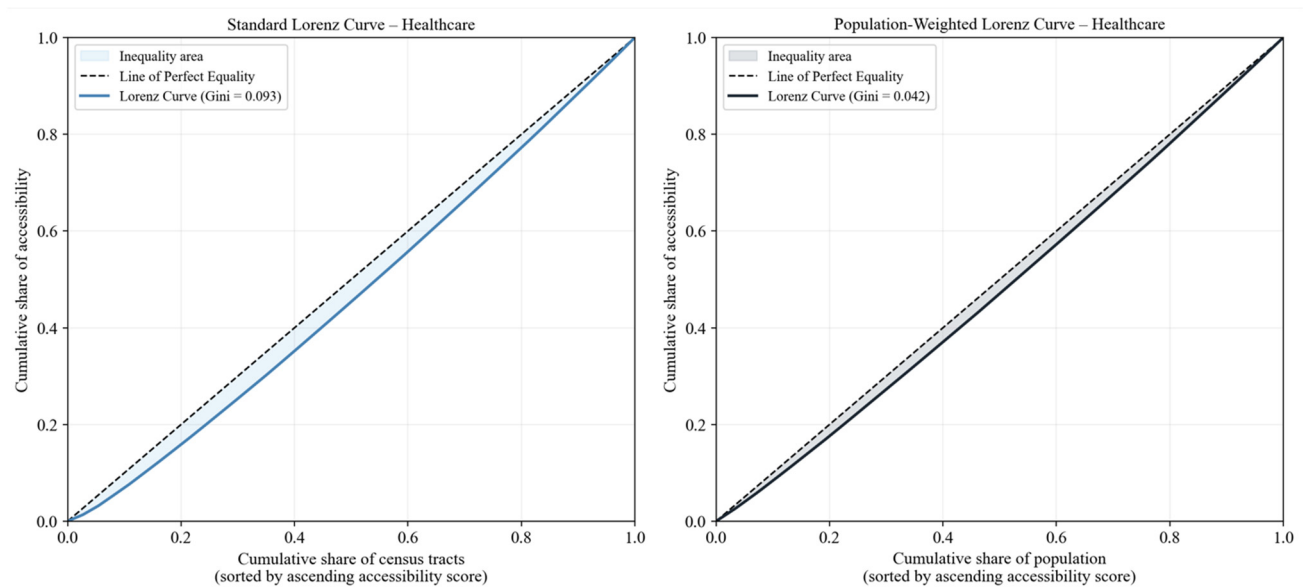


Figure 7. Lorenz curves for healthcare facility accessibility across Fargo's 38 census tracts. The standard ((left) Gini = 0.093) and population-weighted ((right) Gini = 0.042) curves both fall below the line of perfect equality, indicating unequal distribution of healthcare accessibility.

5.4. Park Accessibility

The OD matrix analysis yielded 3496 origin-destination pairs across 38 census tracts and 92 park locations, using road network-based nearest-facility assignment in which every tract was guaranteed coverage by its nearest park. Network distances to the nearest park ranged from 0.14 miles to 6.94 miles, with a mean of 0.93 miles and a median of 0.52 miles (Figure 8). Figure 9 illustrates the shortest-path road network routes from each tract centroid to its nearest park, confirming the dense, dispersed coverage of park infrastructure throughout the city. The strongly right-skewed distribution indicates that the majority of tracts are very well served, with 34 of 38 tracts lying within 2 miles of the nearest park; a small number of peripheral tracts experience substantially longer travel distances. The most isolated tract requires a network distance of 6.94 miles to reach the nearest park.

Normalized accessibility scores ranged from 0 to 1 with a mean score of 0.882—the highest of the three amenity categories. The standard Gini coefficient for park accessibility was 0.081, and the population-weighted Gini was 0.029, both the lowest of the three amenity types, confirming that park access is distributed most equitably across Fargo's census tracts. The bottom quartile of accessibility scores includes 10 census tracts with a combined population of 7704 residents, representing 6.4% of the study-area population.

Figure 10 presents the standard and population-weighted Lorenz curves for park accessibility, plotted on separate axes to ensure valid visual comparison. Of the three amenity categories, both panels show the smallest deviation from the line of perfect equality, consistent with parks recording the lowest Gini coefficients of the three amenity types. Nonetheless, the persistent gap between each curve and the equality line confirms that meaningful spatial inequality in park accessibility remains even in Fargo's most equitably distributed amenity dimension.

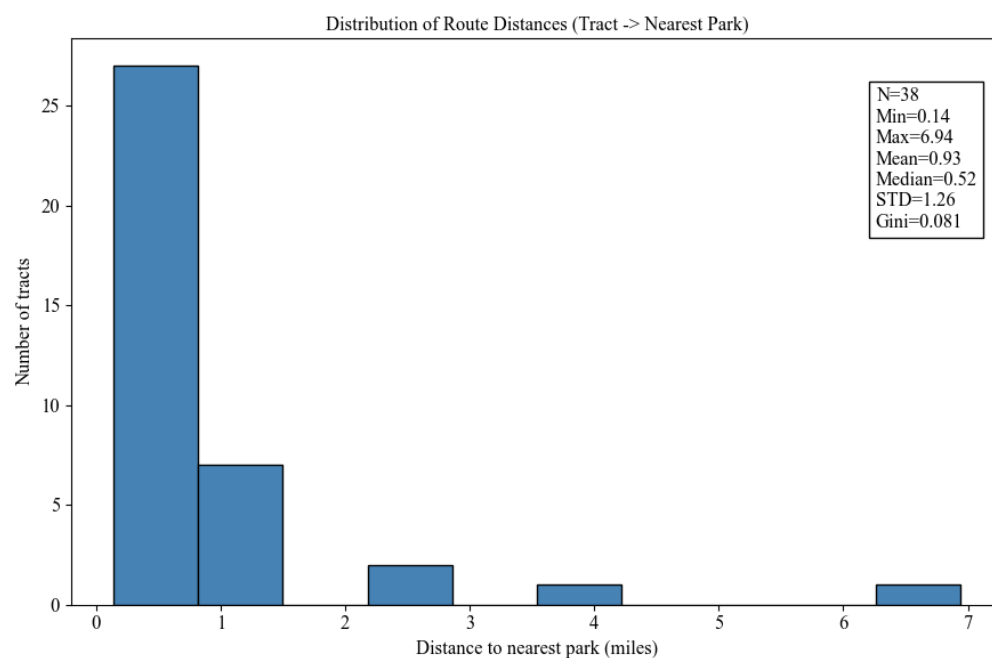


Figure 8. Distribution of road network distances from Fargo census tract centroids to nearest park ($N = 38$). The strongly right-skewed distribution indicates that most tracts are within 1 mile of a park, reflecting the dispersed distribution of the Fargo Park District's 92 park locations. Source: Authors' calculations.

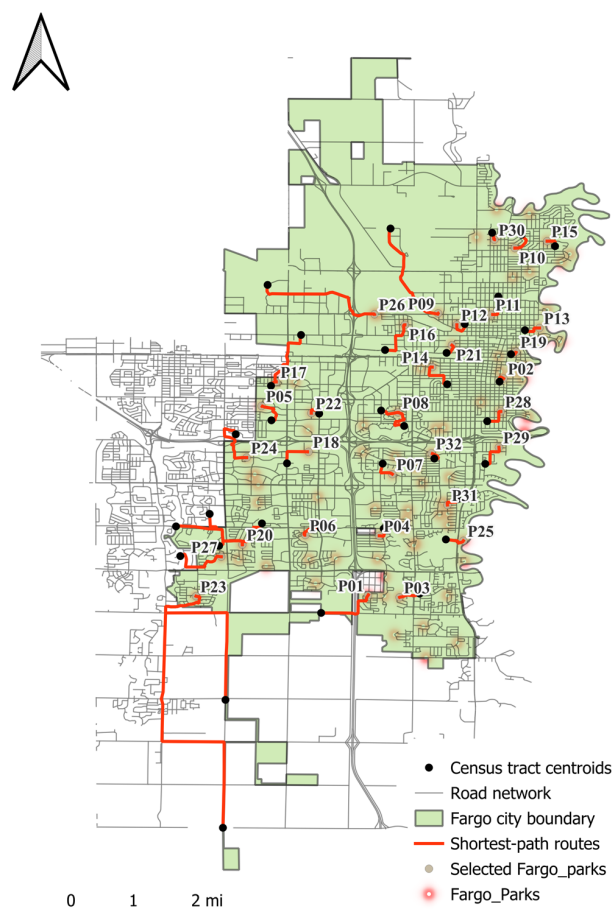


Figure 9. Park accessibility in Fargo, North Dakota. Routes connect 38 census tract centroids to their nearest parks (identified by P-prefixed labels) based on road-network distance. Of the 92 park locations

included in the analysis, 32 were selected as the nearest destination for at least one tract. The outlined boundary denotes Fargo's city limits. Source: Authors' analysis. Coordinate reference system: NAD83 geographic coordinate system (EPSG:4269). Scale bar in miles. North arrow indicates geographic north.

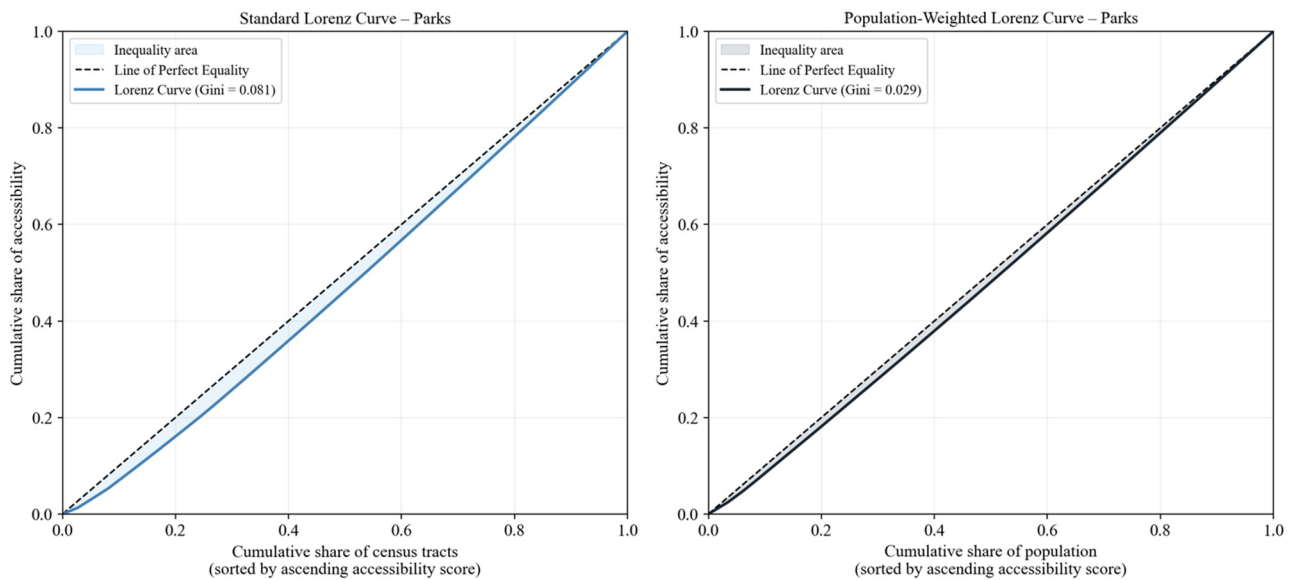


Figure 10. Lorenz curves for park accessibility across Fargo's 38 census tracts. The standard ((left) Gini = 0.081) and population-weighted ((right) Gini = 0.029) curves show the smallest deviation from the line of perfect equality among the three amenity categories, indicating the most equitable distribution of accessibility.

5.5. Composite Accessibility Index

CAI scores ranged from 0 to 0.981, with a mean of 0.856 and a median of 0.908 (Figure 11). The best-served census tract (GEOID: 38017000700) achieved a CAI of 0.981, with consistently high scores across all three amenity dimensions and a resident population of 1605. The worst-served tract (GEOID: 38017040600) received a CAI of 0.000, reflecting low observed accessibility across all three amenity categories simultaneously. Only 0.05% of this tract's land area lies within Fargo's city limits, so its full ACS population of 3463 is not reported here (see Section 6.6). The standard Gini coefficient for the CAI was 0.082, and the population-weighted Gini was 0.029. The bottom quartile of composite accessibility encompasses 10 tracts with a combined population of 9713 residents, 8.0% of the study-area population. For transparency, excluding the tract that occupies only 0.05% of the study area reduces the estimated number of residents in the bottom quartile across all three amenity categories from 9713 to 9711—a difference of two residents (0.02%). This negligible change does not affect the substantive interpretation of the findings.

Figure 12 presents the standard and population-weighted Lorenz curves for the CAI, plotted on separate axes. Both panels show a similar pattern of moderate deviation from the line of perfect equality, consistent with a Gini coefficient that falls between the lowest (parks) and highest (healthcare) values observed among the individual amenity categories.

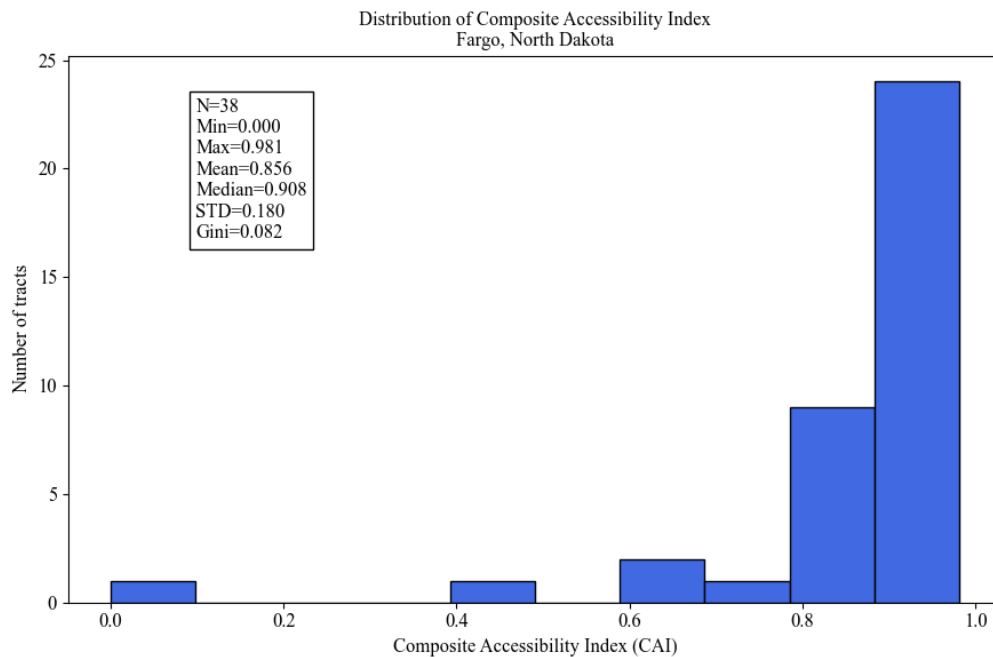


Figure 11. Distribution of the CAI across Fargo census tracts ($N = 38$). The left-skewed distribution indicates that most tracts achieve high composite accessibility, while a small number of peripheral tracts including one with a CAI of 0 receive substantially lower scores. Source: Authors' calculations.

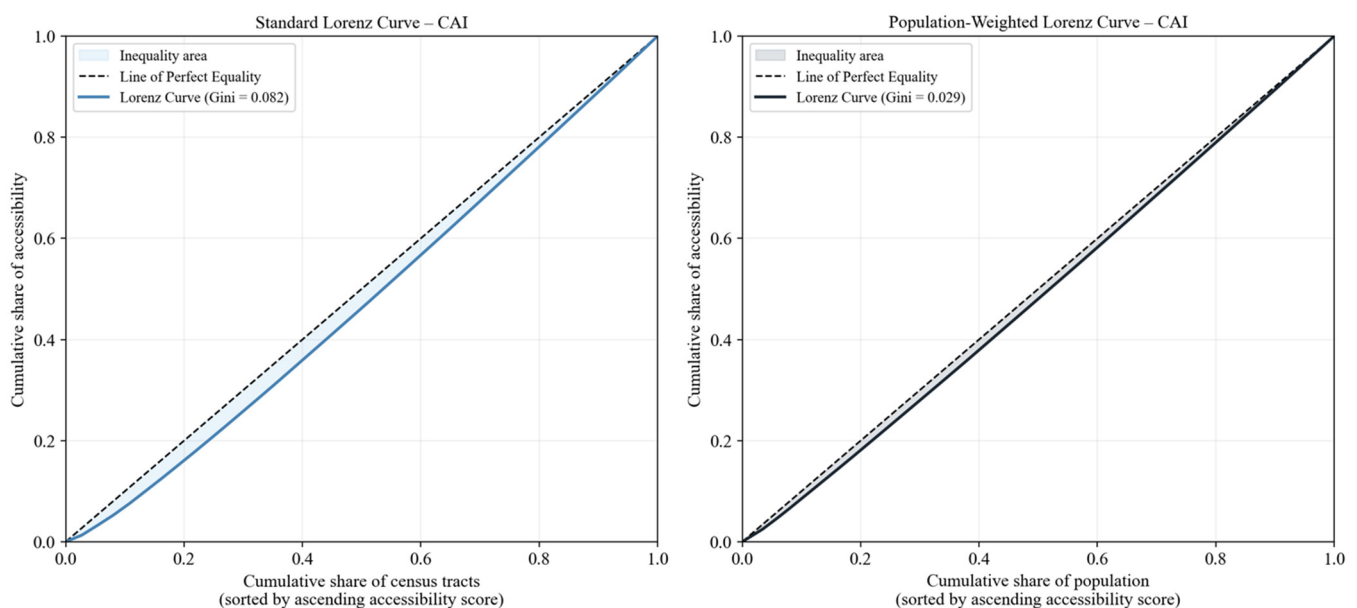


Figure 12. Standard (left) and population-weighted (right) Lorenz curves for the CAI across Fargo census tracts ($N = 38$), plotted on separate axes (tract share vs. population share). Gini = 0.082 (standard); 0.029 (population-weighted). Source: Authors' calculations.

Figure 13 compares accessibility scores across all three amenity categories and the composite index for each census tract, sorted by CAI. The component scores track closely together for most tracts but diverge most visibly in the lowest-scoring tracts, where healthcare consistently registers the lowest scores—consistent with healthcare's higher Gini coefficient—while parks consistently register the highest scores among the three amenities across the accessibility spectrum.

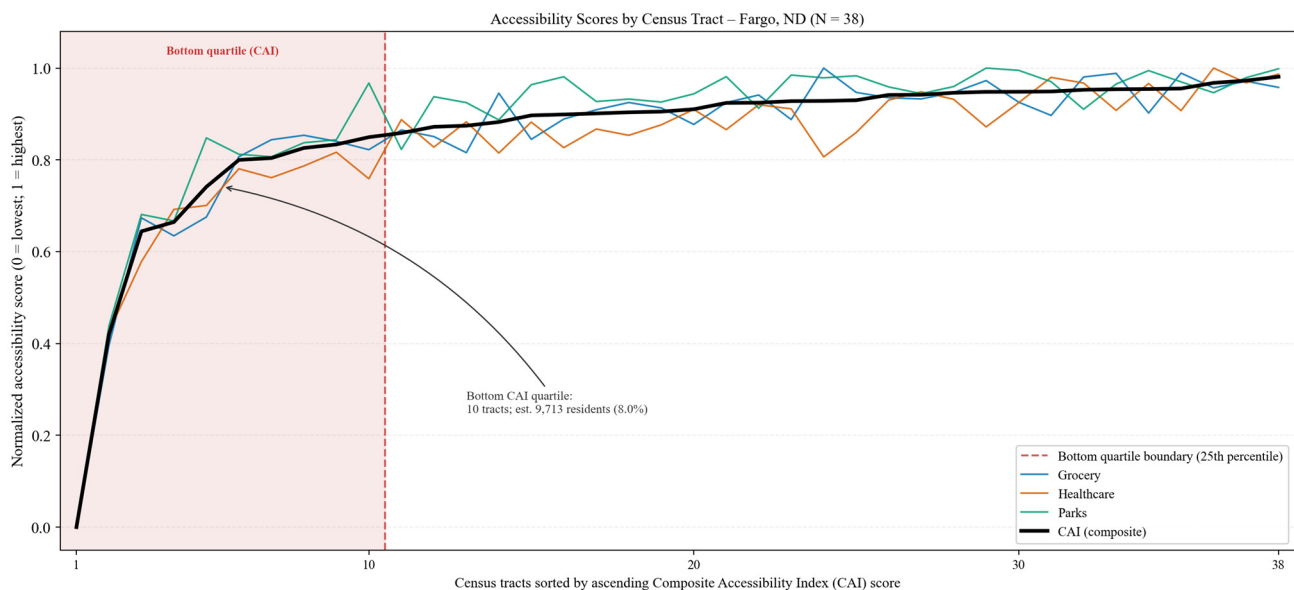


Figure 13. Accessibility scores for grocery, healthcare, and park amenities, and the CAI, by census tract ($N = 38$), sorted by ascending CAI. Healthcare consistently registers the lowest scores and parks the highest among the three amenity categories. Source: Authors' calculations.

5.6. Comparative Analysis

Table 2 summarizes the key distributional statistics for all four accessibility measures, including bootstrap 95% confidence intervals for all Gini coefficients. Standard Gini coefficients range from 0.081 (parks) to 0.093 (healthcare), while population-weighted Gini coefficients are lower across all measures, ranging from 0.029 (parks and CAI) to 0.042 (healthcare). These values indicate modest citywide accessibility inequality. Their policy relevance lies primarily in the geographic concentration of relatively longer travel distances in a small number of peripheral tracts rather than in a high overall magnitude of inequality. In every case, the population-weighted Gini was roughly half or less of the standard Gini, indicating that the least-accessible tracts tend to have smaller in-city populations. Park accessibility recorded the shortest mean (0.93 miles) and median (0.52 miles) distances (Table 3), reflecting the Fargo Park District's relatively dispersed distribution of neighborhood park facilities. The distance distributions appear right-skewed, as the mean exceeds the median and the maximum is substantially higher than both for each amenity category. This skew suggests that a small number of tracts experience relatively long travel distances. When considered alongside the spatial maps, these high-distance observations are concentrated primarily in peripheral tracts, indicating localized accessibility disadvantages rather than uniformly poor accessibility across Fargo.

Table 2. Global Moran's I results for amenity accessibility and the composite accessibility index across Fargo's 38 census tracts.

Measure	Moran's I	Permutation z-Score	Two-Sided Permutation p -Value	Holm-Adjusted p -Value
Grocery	0.4121	5.628	0.0001	0.0004
Healthcare	0.4449	6.043	0.0001	0.0004
Parks	0.3801	5.405	0.0001	0.0004
CAI	0.4241	5.993	0.0001	0.0004

Table 3. Spatial accessibility statistics by amenity type, Fargo census tracts ($N = 38$). Accessibility scores are normalized on a 0–1 scale (0 = lowest, 1 = highest). SD = standard deviation; IQR = interquartile range ($Q3 - Q1$). High SD values relative to means reflect right-skewed distance distributions driven by a small number of peripheral tracts. Gini coefficients measure distributional inequality (0 = perfect equality). Underserved tracts are defined as the bottom 25% of accessibility scores. Source: Authors’ calculations based on using road network-based nearest-facility assignment.

Metric	Grocery	Healthcare	Parks	CAI
Min distance (miles)	0.23	0.15	0.14	-
Max distance (miles)	7.77	7.16	6.94	-
Mean distance (miles)	1.33	1.33	0.93	-
Median distance (miles)	0.94	1.03	0.52	-
SD distance (miles)	1.39	1.26	1.26	-
IQR distance (miles)	0.77	0.80	0.81	-
Mean accessibility score	0.854	0.831	0.882	0.856
95% CI (standard)	0.043, 0.151	0.048, 0.154	0.036, 0.143	0.037, 0.144
95% CI (pop-weighted)	0.024, 0.057	0.029, 0.055	0.015, 0.047	0.017, 0.046
Standard Gini	0.088	0.093	0.081	0.082
Population-weighted Gini	0.040	0.042	0.029	0.029
Underserved population	15,118	13,441	7704	9713
Underserved population (%)	12.5%	11.1%	6.4%	8.0%

Bootstrap 95% confidence intervals overlapped across all four measures, indicating that differences in Gini values should be interpreted as descriptive point estimates rather than statistically confirmed rankings given the small number of tracts ($N = 38$). All four measures exhibited significant positive spatial autocorrelation: grocery ($I = 0.4121$), healthcare ($I = 0.4449$), parks ($I = 0.3801$), and CAI ($I = 0.4241$), with Holm-adjusted $p = 0.0004$ throughout. Neighboring tracts therefore tended to have similar accessibility scores, although global Moran’s I does not locate specific clusters. CAI rankings were largely stable across five alternative weighting schemes, with Spearman correlations of 0.9759–0.9934 relative to equal weighting (Appendix A (Table A1)). Four alternatives retained all 10 baseline bottom-quartile tracts, while the parks-dominant scheme retained nine. These findings indicate limited sensitivity of tract rankings and bottom-quartile membership to the weighting scenarios tested.

Figure 13 provides a visual comparison consistent with this descriptive ordering, which compares accessibility scores across all three amenity categories alongside the CAI for each census tract, sorted by ascending composite score. Healthcare consistently registered the lowest scores among the three amenities across the bottom half of the distribution, while parks consistently registered the highest scores, visually consistent with the Gini-based point estimates for amenity equity. The CAI tracked closely with the average of the three component scores, falling between healthcare and parks for most tracts, with the gap between component scores widening most noticeably among the lowest-scoring tracts. This pattern suggests that, among the lower-CAI tracts, healthcare accessibility generally contributes more to the composite shortfall than grocery or park accessibility.

Not all facilities within each amenity category were selected as the nearest option for at least one tract. Of the 26 grocery stores, 18 were selected as the nearest store for at least one tract, while 8 were never the closest option for any tract. For healthcare facilities, 22 of 26 were selected, and 4 were never selected. For parks, 32 of 92 were selected, and 60 were never selected. In each case, unselected facilities were excluded from the final assignment because a closer alternative existed for every tract. This outcome is an inherent property of road network-based nearest-facility assignment and does not indicate data error or network connectivity issues.

5.7. Sensitivity Analysis of Underserved Population Thresholds

To assess the robustness of the underserved population estimates to threshold choice, a sensitivity analysis was conducted across seven percentile thresholds ranging from the 10th to the 50th percentile, using the assignment-model results for all four accessibility measures. The selected thresholds span commonly reported definitions of underserved areas while covering conservative through relatively inclusive classifications. Results confirm that the core finding is threshold-independent: regardless of the cutoff applied, a substantial share of Fargo's population experiences below-average composite accessibility. At the most conservative threshold (10th percentile), 4141 residents (3.4%) reside in the lowest-scoring tracts; at the 33rd percentile, this rises to 19,897 residents (16.4%) for the CAI. The four accessibility measures exhibit near-identical sensitivity curves at lower thresholds, confirming that the pattern of spatial disadvantage is consistent across amenity types and not an artifact of the threshold selection. At higher thresholds, the curves diverge modestly, reflecting differences in the population distribution across mid-range accessibility tracts (Figure 14).

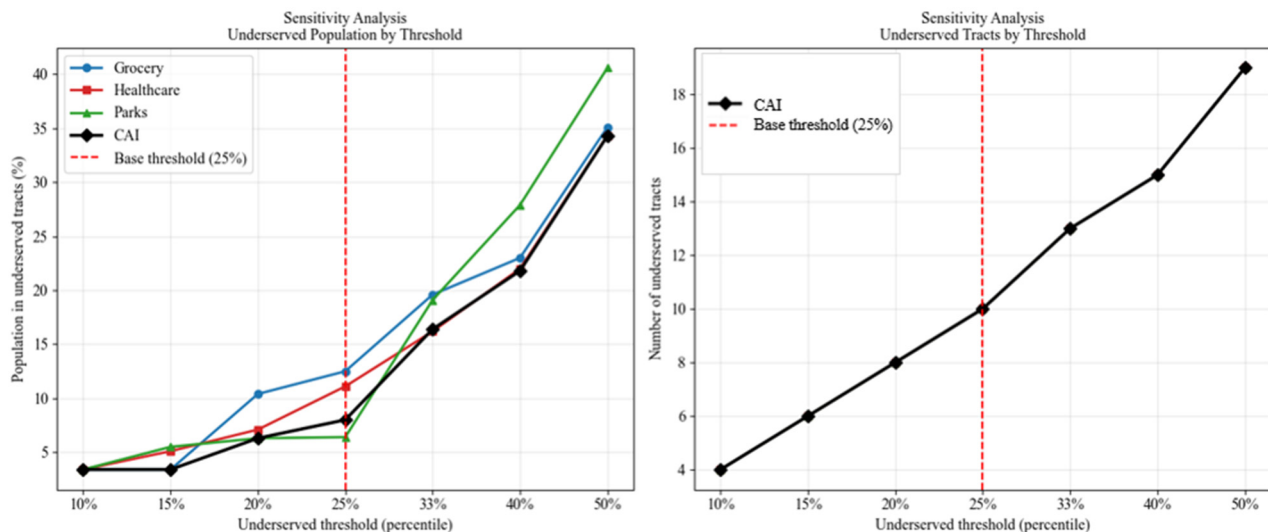


Figure 14. Sensitivity analysis of underserved population estimates across seven percentile thresholds (10th–50th) for all four accessibility measures. The red dashed line indicates the base threshold (25th percentile) used in the primary analysis. Near-parallel trajectories confirm findings are robust to threshold selection. Source: Authors' calculations.

5.8. Spatial Distribution of Composite Accessibility Disadvantage

The bottom CAI quartile comprises the 10 census tracts with the lowest average normalized accessibility scores across grocery stores, healthcare facilities, and parks. Together, these tracts contain an estimated 9713 residents, representing 8.0% of the adjusted study-area population. Low composite scores can reflect different combinations of amenity-specific accessibility scores; membership in the bottom CAI quartile does not necessarily indicate low accessibility in all three categories simultaneously. The reported population therefore represents residents of tracts with relatively low composite accessibility (Table 2), rather than a population demonstrated to experience simultaneous disadvantage across all three amenity categories.

6. Discussion

6.1. Overview

The findings show that favorable citywide livability rankings coexist with modest overall accessibility inequality and localized accessibility disadvantages in some peripheral

tracts. These neighborhood-level findings complement aggregate assessments by describing the spatial distribution of access to essential amenities. This section interprets the results in relation to the existing literature, discusses their planning implications, and acknowledges the study's limitations.

6.2. Aggregate Rankings Versus Neighborhood Reality

The central finding of this study, that approximately 8.0% of Fargo's study-area population resides in census tracts with the lowest composite accessibility scores, directly supports the growing scholarly critique of aggregate livability indices [8,21]. Fargo's exceptional livability score of 85 out of 100 on AreaVibes (2025), ranking it first among all North Dakota cities and better than 97% of U.S. communities, and its LivScore of 716 out of 1000 on Livability.com (2026) reflect genuine citywide strengths in employment, healthcare infrastructure, and quality of life. However, these aggregate scores can obscure localized center-periphery differences in accessibility, with central tracts generally better served than some tracts along the southern periphery. Fargo's localized center-periphery pattern is consistent with findings from other medium-sized cities. In Odense, Denmark, lower accessibility to public amenities was concentrated particularly in peripheral neighborhoods despite the city's compact form and well-developed multimodal transportation system [64]. Similarly, an analysis of Koszalin, Poland, identified weaker access to healthcare, retail, green spaces, and other essential services in some peripheral areas [65]. These comparisons suggest that localized peripheral accessibility gaps are not unique to Fargo and may arise when urban expansion occurs beyond the areas in which services are concentrated. These comparisons are necessarily qualitative rather than numerical because neither the Odense study nor the Koszalin study reported a Gini coefficient directly comparable with the accessibility-inequality estimates calculated for Fargo. In addition, the studies differ in travel modes, spatial units, facility definitions, and accessibility measures. The comparison therefore focuses on the shared center-periphery pattern of accessibility disadvantage rather than on the magnitude of inequality across cities.

The lowest-accessibility tract (GEOID 38017040600), located on Fargo's southern fringe, recorded a CAI of 0.000 (see Section 5.5). However, only 0.05% of its land area lies within Fargo. Applying the area-weighted interpolation produces an estimated in-city population of approximately two residents. Because the available ACS demographic estimates describe the entire tract, they cannot reliably characterize residents within this very small portion of Fargo. A dedicated demographic profile would therefore be misleading and is not reported. Accordingly, the tract's CAI is interpreted as a geographic accessibility result rather than evidence of demographic or social disadvantage. The broader pattern of lower accessibility scores across several southern peripheral tracts, rather than this marginal tract alone, supports the finding of localized peripheral accessibility differences [24,28].

6.3. Amenity-Specific Inequality Patterns

The comparative analysis across the three amenity categories reveals important differences in the spatial distribution of accessibility inequality. Healthcare accessibility exhibited the highest Gini coefficient (0.093) of the three amenity types, reflecting the more spatially concentrated nature of healthcare provision relative to food retail and parks. This finding is consistent with [28,63], noting that healthcare facilities tend to cluster in accessible, high-traffic locations that maximize institutional catchment areas rather than distributional equity. The concentration of Fargo's healthcare infrastructure along the central corridor, anchored by Sanford Medical Center, Essentia Health-Fargo, and the Fargo Veterans Administration Medical Center, produces strong accessibility for centrally located tracts but leaves peripheral tracts significantly underserved.

Park accessibility exhibited the lowest Gini coefficient (0.081) of the three amenity types, reflecting the Fargo Park District's relatively dispersed distribution of neighborhood park facilities throughout the city. With 92 park locations distributed across the urban area, the park network provides more geographically equitable coverage than either food retail or healthcare provision. This finding supports [31], who argue that the quantity of green space is a meaningful predictor of accessibility equity when facilities are spatially distributed rather than concentrated. However, the persistence of the southern peripheral tract as the worst-served location even in the most equitable amenity category highlights that no single sector of amenity provision has adequately addressed the access needs of Fargo's fastest-growing outlying neighborhoods.

Grocery accessibility occupied an intermediate position, with a Gini of 0.088 and the highest maximum distance (7.77 miles) of the three amenity types. The diversity of Fargo's grocery retail landscape, encompassing national supercenters, regional chains, and specialty ethnic grocers serving the city's growing immigrant and refugee communities, contributes to relatively broad spatial coverage in the central city. The presence of ethnic grocery stores such as Lotus Blossom Ethnic Asian Grocery, Himalayan Grocery, and the African Market reflects Fargo's demographic diversification over the past two decades and suggests that the private food retail market has responded, at least partially, to the needs of the city's growing minority population. However, this response has been geographically concentrated in established neighborhoods, leaving peripheral growth areas without adequate food retail provision.

6.4. Population-Weighted Gini and Distributional Implications

The consistently lower population-weighted Gini coefficients relative to the standard Gini coefficients across all four measures confirm that the least-accessible tracts in Fargo tend to have smaller in-city populations than the best-served tracts. Following areal-interpolation correction, this pattern is particularly pronounced: population-weighted Gini values (0.029 to 0.042) are approximately half the standard values (0.081 to 0.093), reflecting the geographic reality that several of the lowest-scoring peripheral tracts have only a small fraction of their land area, and correspondingly small populations, actually within Fargo's city limits.

At the 25th percentile threshold, approximately 9713 residents (8.0% of the study-area population of 121,219) reside in the bottom composite accessibility quartile. The spatial pattern of accessibility disadvantage is concentrated in the same 10 peripheral tracts regardless of population weighting. The planning challenge of providing essential amenities to newly developing fringe areas remains real and documented.

If residential growth is concentrated in peripheral tracts with relatively low accessibility and amenity provision does not keep pace, population-weighted accessibility inequality could increase. This represents a potential planning risk rather than a quantified forecast, since the present study does not model future population growth or changes in amenity provision. The observed peripheral accessibility differences are consistent with the broader literature on amenity provision in rapidly growing mid-sized cities [12]. This outcome highlights the need for proactive, equity-oriented planning approaches that anticipate the amenity needs of emerging neighborhoods rather than responding reactively to documented deficits.

6.5. Contributions and Implications

Unlike most spatial accessibility studies that focus on a single amenity type, this study simultaneously evaluates grocery, healthcare, and park accessibility within a unified framework, combining road network-based nearest-facility assignment, a CAI, and

population-weighted Gini coefficients at the census tract level. This multi-amenity approach at fine spatial resolution remains relatively rare in the livability literature, particularly for mid-sized American cities.

The findings carry important implications for both planning practice and livability measurement. Planning agencies that rely solely on aggregate indices to assess urban livability risk overlooking localized accessibility differences within their jurisdictions. A practical response would be for the Fargo Planning and Development Department, in coordination with Fargo Cass Public Health and the Fargo Park District, to publish an annual tract-level accessibility dashboard. The dashboard could report network distances, amenity-specific accessibility scores, the Composite Accessibility Index, and standard and population-weighted Gini coefficients as citywide summaries. Tracts in the bottom accessibility quartile could then be reviewed during comprehensive planning, development review, and capital programming to determine whether zoning incentives, mobile services, or future park development warrant further assessment. Specific investments should also consider demand, cost, facility capacity, and community preferences. The analytical workflow provides a reproducible approach for evaluating neighborhood-level accessibility in comparable mid-sized cities seeking neighborhood-level evidence to inform equity-oriented investment decisions.

The contribution of this study extends beyond the well-established observation that peripheral neighborhoods often experience lower accessibility to essential amenities. Rather, it advances the literature in three important ways. First, it demonstrates that modest city-wide accessibility inequality can coexist with localized disadvantages in a small number of peripheral tracts, even within a city consistently recognized as highly livable by national ranking systems. Second, it evaluates cumulative accessibility disadvantage across multiple amenity categories, grocery stores, healthcare facilities, and parks, within a mid-sized U.S. city, a context that has received limited attention in the spatial accessibility and livability literature, which has largely focused on major metropolitan areas or single-amenity analyses. Third, the study incorporates population-weighted measures of accessibility inequality, enabling the assessment of how many residents are affected by spatial disparities rather than simply how many census tracts exhibit poor access. By integrating network-based accessibility modeling, composite livability measurement, and population-weighted equity assessment, the study offers a more nuanced understanding of neighborhood-level livability than aggregate city rankings alone can provide. Although the empirical findings are specific to Fargo, the methodological framework may be adapted for use in other mid-sized U.S. cities, subject to differences in urban form, data availability, and locally relevant amenity definitions.

6.6. Limitations

First, the analysis measured road network distance to the nearest amenity, assuming car-based travel without accounting for facility capacity, quality, service hours, or the demand generated by competing populations. Travel time was not evaluated, and the road-network layer lacked segment-level speed attributes. The distance-based measures therefore do not capture congestion, intersection delays, or time-of-day variation. Future research could incorporate multimodal transportation networks and capacity-adjusted accessibility measures such as the 2SFCA method. Second, fixed census tract boundaries introduce the Modifiable Areal Unit Problem (MAUP) because tract size, shape, and aggregation can affect observed accessibility patterns [66]. This is relevant in Fargo, where peripheral tracts are larger than central tracts. The Gini coefficients and bottom-quartile population estimates might differ at the block-group or block level. Future research should test alternative spatial units if available.

Population apportionment and centroid specification introduce additional uncertainty. The uniform-density assumption may overestimate or underestimate in-city populations where residential development is uneven, particularly in tracts that intersect Fargo only marginally. Geometric centroids may also lie far from residential concentrations, affecting nearest-facility assignments, network distances, and accessibility scores. Consequently, population-weighted Gini coefficients and estimates of residents in the bottom accessibility quartile may be sensitive to these approximations. Future research should use finer-resolution population data, if available, to refine population apportionment and construct population-weighted centroids for the in-city portions of tracts, then evaluate the sensitivity of accessibility and inequality results to these alternatives. Third, OSM may omit, misclassify, or retain outdated amenity records, and its completeness may vary across locations [67]. If peripheral amenities are less completely mapped, the observed center-periphery differences may be overstated. Visual inspection and duplicate removal reduced these concerns but did not establish completeness. Future studies should cross-validate OSM records with authoritative facility inventories. Fourth, the study does not examine the demographic composition of underserved tracts, which would allow direct assessment of whether accessibility disadvantage disproportionately affects minority or low-income populations [68,69], which is an important direction for future research given Fargo's rapid demographic diversification. Fifth, the equal weighting of the three amenity categories reflected a methodological assumption rather than an empirically derived preference structure. Future research could explore resident-weighted composite indices based on survey data.

7. Conclusions

This study conducted a tract-level spatial accessibility analysis of urban livability in Fargo, North Dakota, examining road network-based access to grocery stores, healthcare facilities, and parks across all 38 census tracts using road network-based nearest-facility assignment, a Composite Accessibility Index, and Gini coefficients of distributional inequality. The principal contribution is demonstrating that favorable city-level livability rankings may coexist with localized neighborhood-level accessibility differences. The study demonstrates that modest citywide inequality can coexist with localized accessibility disadvantages within a city consistently ranked highly livable nationally, with approximately 9713 residents (8.0% of the study-area population) residing in the bottom composite accessibility quartile, concentrated in the same 10 peripheral tracts. It evaluates combined accessibility patterns across grocery, healthcare, and park accessibility within a mid-sized U.S. city, a context largely absent from the literature. It also incorporates population-weighted inequality measures, confirming that the least-accessible tracts tend to have smaller in-city populations. As these peripheral areas develop, accessibility inequality could increase if residential growth substantially outpaces future amenity provision.

Since this study examines a single city, Fargo-specific accessibility patterns should not be generalized directly to other urban contexts. Nevertheless, the methodological framework may be adapted for use in other mid-sized U.S. cities, subject to differences in urban form, population distribution, transportation networks, data availability, and locally relevant amenity definitions. Comparative multi-city applications are needed to determine whether the localized peripheral accessibility patterns observed in Fargo recur elsewhere. The findings nonetheless support complementing city-level livability rankings with neighborhood-scale accessibility assessments when evaluating the distribution of essential amenities.

Author Contributions: Conceptualization, R.P. and R.B.; methodology, R.P. and R.B.; software, R.P. and R.B.; validation, R.P., R.B. and J.S.; formal analysis, R.P. and R.B.; investigation, R.P. and R.B.; resources, J.S.; data curation, R.P. and R.B.; writing—original draft preparation, R.P. and R.B.; writing—review and editing R.P. and R.B.; visualization, R.P. and R.B.; supervision, R.B. and J.S.; project administration, R.B. and J.S.; funding acquisition, R.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The source spatial datasets used in this study are publicly available from the U.S. Census Bureau TIGER/Line files [47], ACS 5-Year Estimates [49], OpenStreetMap through the QuickOSM plugin, the Highway Performance Monitoring System road-network dataset [62], and the City of Fargo ArcGIS Hub [48]. Relevant citations and access links are provided in the reference list. Derived datasets generated during the analysis, including origin–destination matrices, city-adjusted tract population estimates, and tract-level accessibility scores, are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

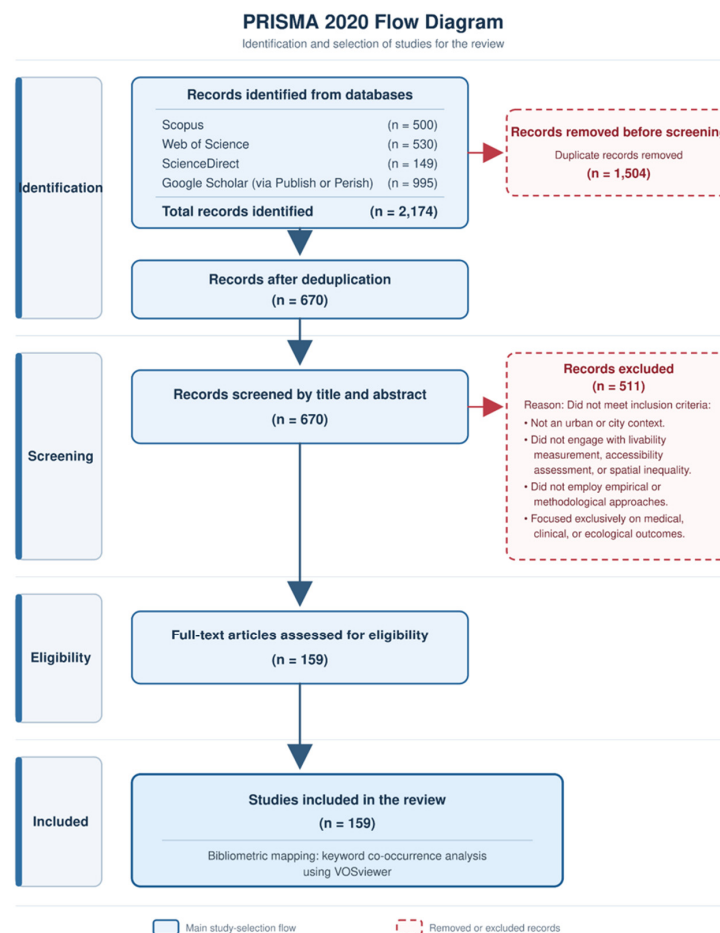


Figure A1. PRISMA 2020 flow diagram showing the identification, screening, eligibility assessment, and final inclusion of studies used in the systematic literature review and VOSviewer bibliometric analysis.

Table A1. CAI weighting sensitivity analysis across Fargo’s 38 census tracts. Note that Spearman correlations compare tract rankings with the equal-weight baseline. Bottom-quartile overlap indicates how many of the 10 baseline bottom-quartile tracts were retained. Alternative weights are analyst-selected sensitivity scenarios, not estimated resident preferences. The grocery–healthcare-only scheme is a stress test excluding parks.

Weighting Scheme	Grocery Weight	Healthcare Weight	Parks Weight	Spearman ρ	Bottom-Quartile Overlap
Equal-weight baseline	1/3	1/3	1/3	1.0000	10/10
Healthcare-dominant	0.25	0.50	0.25	0.9821	10/10
Grocery-dominant	0.50	0.25	0.25	0.9821	10/10
Parks-discounted	0.40	0.40	0.20	0.9934	10/10
Parks-dominant	0.25	0.25	0.50	0.9799	9/10
Grocery–healthcare only	0.50	0.50	0.00	0.9759	10/10

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