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Road-network-based Enhanced Two-step Floating Catchment Area Analysis of Spatial Inequality in Healthcare Access

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In this study, we quantitatively analyzed healthcare accessibility in Asan, Chungcheongnam-do, South Korea, by the enhanced two-step floating catchment area (E2SFCA) method. Healthcare accessibility significantly affects public health and quality of life. However, disparities between urban and rural areas persist. We aimed to evaluate the spatial imbalance in healthcare resources within Asan and to identify medically underserved areas in this study. A node-based road network analysis was conducted to reflect actual resident mobility patterns. We employed the E2SFCA method to compute a healthcare accessibility index and used the Lorenz curve and Gini coefficient to assess the degree of inequality in healthcare accessibility. Subsequently, a cluster analysis using the Louvain algorithm identified 55 communities with similar healthcare accessibility levels. It revealed that urban areas exhibited high healthcare accessibility, whereas peripheral areas had low accessibility. Finally, G_i^* Getis-Ord statistics were used in a hotspot analysis to identify regions with significantly high and low healthcare accessibility levels. The findings suggest that healthcare accessibility is concentrated in urban areas, whereas peripheral regions lack adequate healthcare services. Compared with conventional grid-based approaches, in this study, we more precisely captured actual movement patterns using a road-network-based accessibility analysis. This enabled a more detailed assessment of the spatial disparities in healthcare accessibility. These findings can be foundational for efficiently allocating healthcare resources and developing public health policies.

1. Introduction

Globally, healthcare services are acknowledged as a crucial component of basic public services.[1,2] Healthcare services treat diseases and enhance the overall quality of life through prevention and health promotion. In recent years, the integration of sensor-based data has further enhanced the precision of healthcare accessibility analyses by capturing real-time patient mobility and service utilization patterns.[3,4]

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Thus, it directly impacts individual health, economic productivity, and social stability. In particular, during public health crises such as infectious disease outbreaks, issues become more severe in areas with limited healthcare accessibility.[5,6] Healthcare services must be equitably provided to all members of society as a fundamental component of public safety and social welfare.

However, in many countries, disparities in healthcare services between urban and rural areas remain a critical issue. These disparities are particularly significant among low-income populations and are closely linked to economic and social structures.[7] According to the Organization for Economic Cooperation and Development, health-related inequalities persist in most countries.[8]

During industrialization and urbanization, healthcare resources became concentrated in certain areas. This intensified the differences in healthcare accessibility between urban and rural regions.[9,10] Additionally, economic inequality affects the access to healthcare services. This generates situations where low-income individuals do not receive necessary medical care. Notwithstanding the technological advancements that have improved the quality of healthcare services, significant disparities in accessibility exist across regions and socioeconomic classes.[11] Consequently, the imbalance in healthcare resources has worsened, preventing certain regions and groups from fully benefiting from medical services.

South Korea has also experienced the concentration and imbalance of healthcare resources during its rapid industrialization and urbanization. The income-related disparities in healthcare vary significantly by region. For example, in provinces such as Chungcheongnam-do, the number of physicians per 1000 individuals is over three times lower than that in Seoul. Additionally, although Seoul has the highest accessibility to general hospitals, the accessibility decreases in provincial areas. This further intensifies the regional healthcare inequalities.[12] These disparities increase the economic and social costs and adversely impact the overall healthy life expectancy as regional disparities increase.[13]

In this study, we focused on Asan, Chungcheongnam-do, South Korea. We analyzed the healthcare accessibility at each node to identify medically underserved areas within the region. Through this analysis, the spatial distribution of healthcare resources and accessibility imbalances in Asan were examined. This provides a reference for future public health policy planning.

The paper is structured as follows. In the literature review section, we examine the development of the enhanced two-step floating catchment area (E2SFCA) method and review previous studies to highlight the distinctions of this research. In the data section, we describe the characteristics of the study area (Asan, Chungcheongnam-do) and explain the sources and attributes of the data used in the analysis. In the methods section, we describe in detail the healthcare accessibility assessment approach based on the E2SFCA method, clustering of healthcare accessibility patterns using the Louvain algorithm, and hotspot analysis method using Getis-Ord G_i^* statistics. In the results section, we present the findings on healthcare accessibility disparities using the Lorenz curve and Gini coefficient. Additionally, we present the community detection results from the Louvain algorithm and the spatial patterns identified through a hotspot analysis. In the discussion and conclusions section, we present an interpretation of the results and discuss directions for future research.

2. Literature Review

The E2SFCA method was developed to improve existing healthcare accessibility assessment models. It has been refined by many researchers over the past decades. In early studies, evaluated accessibility was evaluated on the basis of simple distance or travel time measurements. For example, Hansen defined accessibility as opportunities available at a given location relative to other locations and analyzed its impact on land use.(14) However, such methods had limitations in fully reflecting the actual healthcare utilization patterns and socioeconomic factors. To address these limitations, the gravity model was introduced.

The gravity model is used to evaluates accessibility by considering the interactions between healthcare resources and populations. It allows for factors beyond simple distance.(15) However, the model oversimplifies the effects of distance and time, thereby failing to account for nonlinear relationships and various influencing factors. This reduces the precision of healthcare accessibility assessments.(16)

To overcome these issues and improve the accuracy of healthcare accessibility analysis, various alternative models have been proposed. For example, Joseph and Phillips introduced a model that incorporates socioeconomic factors such as the economic status of the population, in addition to simple distance measurements.(17) This approach better reflects actual disparities in healthcare accessibility and was developed to overcome the limitations of conventional distance-based calculations.(17) These models have provided a critical foundation for analyzing the socioeconomic impact of healthcare accessibility.

In the early 2000s, Radke and Mu proposed the two-step floating catchment area (2SFCA) method to address the limitations of conventional gravity models and accessibility measurement techniques, which was subsequently refined by Luo and Wang for healthcare accessibility assessment.(18,19) The 2SFCA method is used to evaluate healthcare accessibility in two steps. In the first step, the physician-to-population ratio is calculated within a defined distance around each healthcare facility. In the second step, healthcare accessibility is assessed for each population location within a specified distance. This method was adopted rapidly in healthcare accessibility research owing to its simplicity and convenience of interpretation. However, it has limitations in that it applies a uniform weight to distance and travel time.

To address these shortcomings, Luo and Qi proposed the E2SFCA method as an improvement over 2SFCA.(20) E2SFCA modifies the original 2SFCA structure by incorporating a distance decay function. This enables the accessibility weights to vary based on distance even within a catchment area.(21) The method enables a more precise evaluation of healthcare accessibility by considering distance- and time-based weighting. This makes it particularly reliable for studies on urban healthcare accessibility.(22,23) E2SFCA has also been extended to assess accessibility in a multidimensional manner by incorporating additional variables such as socioeconomic factors, population density, and service quality.(24–28)

In this study, we applied the E2SFCA method to analyze the healthcare accessibility in Asan, South Korea, using a road-network-based approach.(20) The E2SFCA method is used to evaluates healthcare accessibility by simultaneously considering the distribution of medical resources and accessibility for residents. This allows for a more precise analysis using a road network rather than simple distance-based measurements. The approach enables a more accurate understanding of the spatial distribution of healthcare resources and the actual disparities in accessibility across regions. To interpret the accessibility results, Louvain-algorithm-based clustering and hotspot analysis were employed.[29,30] The Louvain algorithm identified the regional patterns in healthcare accessibility by clustering areas with similar characteristics. Meanwhile, the hotspot analysis visualized the concentration of healthcare services, thereby clearly revealing the spatial disparities in accessibility.

Through this comprehensive approach, we have provided a more refined and holistic evaluation of healthcare accessibility compared with previous research. Thereby, our approach has provided effective insights for future studies and policy analysis.

3. Study Area and Data

We selected Asan, Chungcheongnam-do, South Korea, as the study area (Fig. 1). The total area of Asan is 542.8 km^2. As of 2021, its population was 351618. Asan is located near the Seoul metropolitan area. It has experienced continuous population growth and urbanization as a key industrial hub. Additionally, in 2021, its per capita Gross Regional Domestic Product was KRW 91.1 million, which significantly exceeded the national average of KRW 40.27 million.[31]

Notwithstanding this high economic growth, the number of healthcare facilities, pharmacies, and general hospitals per 100000 individuals in Asan is below the average for Chungcheongnam-do. This reveals a relatively low and vulnerable healthcare accessibility. This indicates the need for expanding the local healthcare infrastructure to accommodate the ongoing population growth and aging. In particular, the nonuniform distribution of medical resources between urban centers and peripheral areas can intensify healthcare accessibility issues for the elderly and vulnerable populations.

Considering these characteristics, Asan serves as a suitable study area for analyzing the healthcare accessibility challenges related to aging and vulnerable populations. On the basis of this background, Asan was selected as the study area for analyzing medically underserved regions.

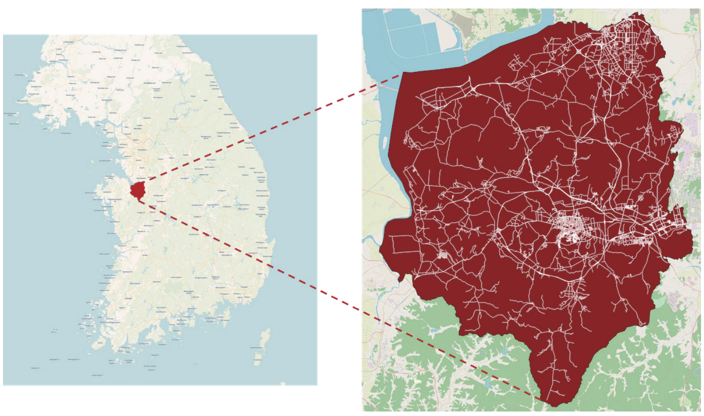


Fig. 1. (Color online) Study area.

The experimental data for this study were obtained using built-in Python programs such as OpenStreetMap (OSM) and HealthMap, and the National Spatial Information Platform. We used OSM's detailed road network of Asan and the population grid data and mapping grid data provided by the National Spatial Information Platform.

We also used Asan hospital information and hospital specialties information provided by HealthMap. A description of the data is provided in Table 1. Additionally, the total number of nodes in the road network used for the analysis is 6451, with a total of 16205 links.

4. Methods

We assessed the healthcare accessibility in Asan, Chungcheongnam-do, South Korea, by the E2SFCA method. The Louvain algorithm was then applied to cluster regions with comparable levels of healthcare accessibility. This was followed by a hotspot analysis to examine the spatial distribution patterns.

4.1 E2SFCA

The E2SFCA method was employed to analyze the healthcare accessibility in Asan, Chungcheongnam-do. The E2SFCA method operates in two stages.[20]

Stage 1: The catchment area for a physician location j includes all the regions within a 30 min driving distance. Within each catchment, three travel time zones (0–10, 10–20, and 20–30 min) are defined. The model identifies all the population locations (k) within a given threshold travel time zone (D_r) and calculates the weighted physician-to-population ratio (R_j) within the catchment area.

$$R_j = \frac{S_j}{\sum_{k \in \left\{d_{kj} \in D_r\right\}} P_k W_r} \tag{1}$$

Here, S_j represents the number of physicians at location j, P_k denotes the population of grid cell k located within the catchment area, j ($d_{kj} \le D_r$), d_{kj} represents the travel time between k and j, and D_r denotes the rth travel time zone within the catchment area (r = 1–3). W_r represents the distance weight for the rth travel time zone. It is calculated using a Gaussian function, which accounts for the distance decay effect in physician accessibility.

Table 1
Description of data.

Name	Description	Data type
Asan Population Grid	Reference year, population count	csv
Asan Grid (for mapping)	Asan 100 × 100 m^2 grid	geojson
Asan Hospital Information	Hospital name, total number of physicians, longitude, latitude	csv
Asan Hospital Specialties Information	Hospital name, specialty name, number of specialists per specialty	csv

Stage 2: All the physician locations j within a 30 min travel time from each population location i are identified, and the physician-to-population ratio R_j calculated in Stage 1 is aggregated.

$$A_i^F = \sum_{j \in \{d_{ij} \in D_r\}} R_j W_r = \sum_{j \in \{d_{ij} \in D_1\}} R_j W_1 + \sum_{j \in \{d_{ij} \in D_2\}} R_j W_2 + \sum_{j \in \{d_{ij} \in D_3\}} R_j W_3 \tag{2}$$

Here, A_i^F represents the healthcare accessibility at location i and R_j denotes the physician-to-population ratio at physician locations j within the catchment area of population location i. d_{ij} represents the travel time between i and j. The distance weights derived from the Gaussian function used to calculate R_j are applied to different travel time zones. These reflect the distance decay.

Typically, the E2SFCA method is used to evaluate accessibility on the basis of grid-based analysis. However, we assessed the accessibility at the node level within the road network. This approach was selected for the following reasons. First, node-based analysis provides a more intuitive representation of urban characteristics. Areas with high node density in the road network are likely to be urban centers. This allows for a clearer identification of spatial accessibility patterns. Second, in grid-based analysis, accessibility values tend to be overestimated in areas with negligible or no captured population. This hinders the assessment of the relative importance of different regions. In contrast, node-based analysis mitigates this issue and provides a more precise spatial representation of accessibility by considering the actual network locations of each node.

4.2 Community detection

The Louvain algorithm was used to analyze the spatial patterns of healthcare accessibility by clustering regions based on similarity. It operates by maximizing the network modularity. This makes it highly effective in detecting naturally occurring communities within a network.[29] In this study, healthcare accessibility was evaluated on the basis of road network nodes. Regions with similar accessibility levels were clustered into communities.

In the first step of the Louvain algorithm, each node is initially considered an independent community. Moreover, nodes are reassigned to increase the modularity on the basis of the strength of connections with adjacent nodes. This process is repeated until no further increase in modularity is observed. In the second step, the previously formed communities are considered as single nodes, a new network is constructed, and the first step is reapplied. Through these iterative steps, the final community structure is derived. This maximizes the modularity.

4.3 Hotspot analysis

To gain a more detailed understanding of the spatial distribution of healthcare accessibility, a hotspot analysis was conducted using Getis-Ord G_i^* statistics.[30] This statistical method identifies spatial clustering patterns by evaluating whether a given region's values are significantly higher or lower than those of the surrounding areas. The analysis was based on the healthcare accessibility index (A_i) derived from the E2SFCA method.

The analysis procedure was as follows: First, a spatial weight matrix was established to account for the spatial proximity between nodes. To assess the similarity of healthcare accessibility values among adjacent nodes, the k-nearest neighbors (k = 5) method was applied. Next, the Getis-Ord G_i^* statistic was calculated for each node to determine whether its healthcare accessibility value was statistically different from those of the neighboring nodes. Only the results with p-value < 0.05 were considered statistically significant.

5. Results

In this study, we focused on analyzing the spatial distribution and clustering characteristics of healthcare accessibility in Asan. Specifically, the spatial inequality of healthcare accessibility was assessed quantitatively, regions with similar accessibility patterns were clustered, and areas with concentrated or insufficient healthcare services were identified.

First, the E2SFCA method was applied to calculate the healthcare accessibility values, and the Lorenz curve and Gini coefficient were used to evaluate the degree of accessibility inequality. Next, the Louvain algorithm was applied to cluster regions with similar healthcare accessibility values, and a hotspot analysis was conducted to examine spatial correlations.

Unlike conventional grid- or administrative-district-based analyses, we assessed accessibility on the basis of road network nodes. This approach is differentiated from previous research by reflecting the actual movement patterns of residents. This allows for a more realistic assessment of healthcare accessibility.

Additionally, in the E2SFCA analysis, weights (1.00, 0.68, and 0.22) were applied to three travel time intervals (0–10, 10–20, and 20–30 min). This weighting system accounts for the gradual reduction in healthcare accessibility over distance and time. Thus, it effectively models real-world healthcare utilization behaviors.

Through this methodological distinction, we performed a more precise and reliable assessment of healthcare accessibility. Thereby, we provided insights into the spatial characteristics of Asan, Chungcheongnam-do, South Korea.

5.1 Exploratory global inequality

We quantitatively evaluated the spatial inequality of healthcare accessibility in Asan using $\boldsymbol{A_i}$ values determined by the E2SFCA method. Specifically, the Lorenz curve and Gini coefficient were applied to analyze whether healthcare accessibility was concentrated in specific areas. The Gini coefficient is a widely used measure of inequality in asset distribution. It is based on the concept of cumulative wealth distribution.[32] This coefficient is closely related to the Lorenz curve, which graphically represents the cumulative proportion of wealth held by a given percentage of the population. For example, in a society with extreme wealth inequality, the Lorenz curve initially increases gradually and then increases abruptly when the highest-income group is included.

Figure 2 shows the Lorenz curve for healthcare accessibility in Asan. Compared with the perfect equality line (red), the Lorenz curve (blue) bends downward. This phenomenon is

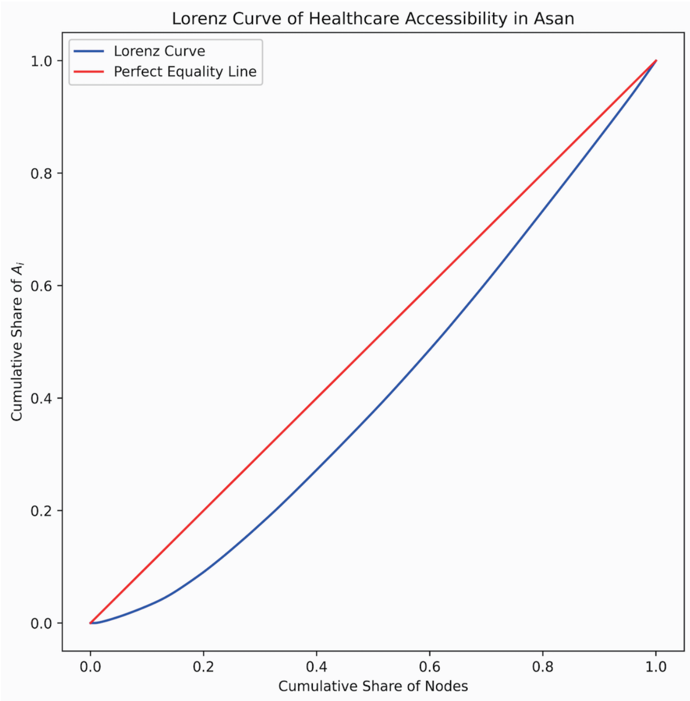


Fig. 2. (Color online) Lorenz curve of healthcare accessibility in Asan.

observed when a significant portion of the population resides in areas with low healthcare accessibility. Additionally, the Gini coefficient for healthcare accessibility in Asan was calculated as 0.1756. The value indicates regional disparities in accessibility.

To further analyze this spatial inequality, the Louvain algorithm was used to cluster regions with similar healthcare accessibility levels, and a hotspot analysis was performed to examine the spatial correlations.

5.2 Community detection

Community detection techniques were applied to analyze the spatial patterns of healthcare accessibility data. This allowed for the clustering of regions. Specifically, the Louvain algorithm was used. It maximizes network modularity to effectively cluster regions with similar characteristics. This algorithm identified a total of 55 communities, as shown in Fig. 3.

The number of nodes per community ranged from 28 to 326, which revealed a considerable variation in size. The differences in community size reflect regional characteristics, particularly variations in connectivity and accessibility between urban and peripheral areas. The largest community (Community 15) contained 326 nodes. This indicated a high connectivity within the network.

The average healthcare accessibility across communities ranged from 0.000 to 0.002. This highlighted the significant disparities between communities. The communities with the highest average accessibility were Community 7 (2.061×10^{-3}), Community 24 (2.047×10^{-3}), and Community 25 (2.007×10^{-3}). These are located in urban areas. In contrast, the communities

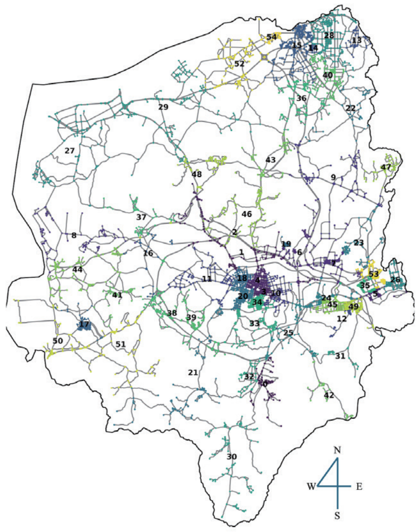


Fig. 3. (Color online) Asan City community.

with the lowest average accessibility—Community 30 (4.4×10^{-4}), Community 27 (5.38×10^{-4}), and Community 8 (5.43×10^{-4})—are located in the southwestern peripheral areas. This indicated low access to healthcare services in these regions.

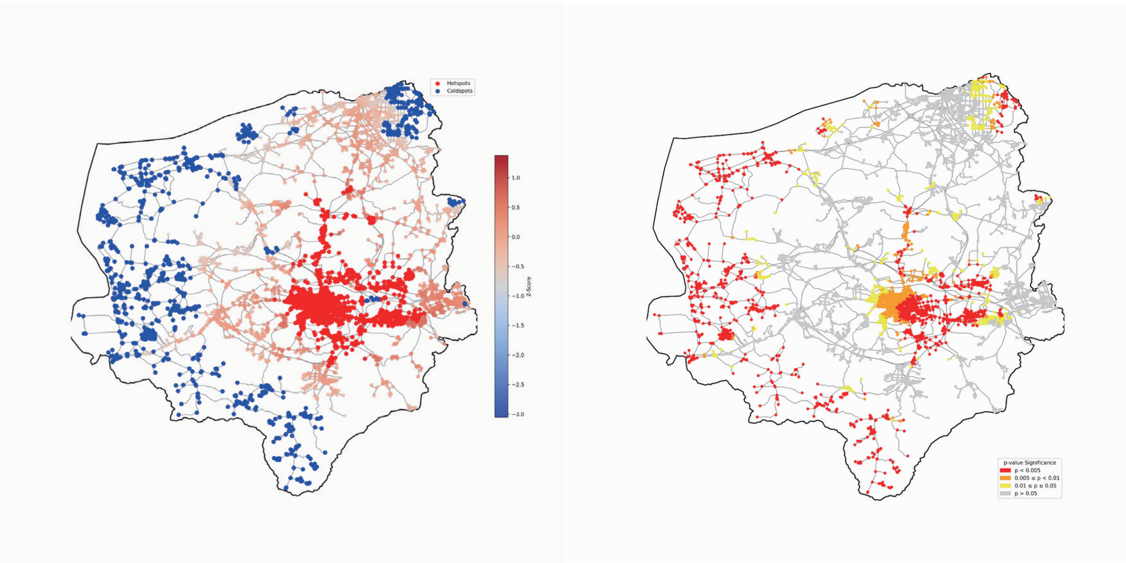
5.3 Hotspot analysis

The spatial concentration of healthcare accessibility in Asan was analyzed using the Getis-Ord G_i^* statistic. This statistic was applied to determine whether a region's accessibility value was statistically significantly higher or lower than that of surrounding areas. Figure 4(a) visualizes the results of this analysis using *z*-scores. Here, statistically significant (i.e., p-value < 0.05) high-accessibility regions are shown in red, whereas low-accessibility regions are shown in blue. The analysis revealed that central areas exhibited high *z*-scores, thus indicating a relative concentration of healthcare accessibility. Additionally, Fig. 4(b) shows the statistical significance levels of hotspot and coldspot regions based on *p*-values. These results indicate that the healthcare resources in Asan are concentrated in certain areas, whereas peripheral regions confront accessibility challenges.

6. Discussion and Conclusions

The results of this study clearly indicate spatial disparities in healthcare accessibility in Asan. In particular, using road network nodes for accessibility assessment enabled a more precise analysis.

In previous E2SFCA-based studies, accessibility was generally assessed using grids or administrative units. However, such approaches may include areas where humans do not actually



(a) (b)

Fig. 4. (Color online) (a) Hotspot and coldspot analyses (p-value < 0.05) and (b) significance levels using p-values.

reside (e.g., mountains and rivers). This results in unrealistic assessments. To overcome this issue, we modeled the road network as a graph and minimized the errors caused by uninhabited areas through noise reduction. As a result, the findings are closely aligned with actual healthcare service access routes.

The results of the community analysis using the Louvain algorithm reflect significant differences in healthcare accessibility between urban and peripheral areas. Urban clusters contain more densely connected nodes, whereas clusters in peripheral areas are more dispersed. This effectively visualizes the high accessibility in urban areas and low accessibility in peripheral areas, thereby providing fundamental data for addressing regional disparities in future healthcare policies.

The hotspot analysis indicated that the high healthcare accessibility in urban areas is attributable to the concentration of medical resources and well-developed transportation infrastructure. This indicates that urban areas have more convenient access to hospitals, pharmacies, and other essential healthcare services. In contrast, peripheral areas exhibit lower accessibility owing to the underdeveloped road networks or limited distribution of medical resources. This indicates that the imbalance in healthcare resource distribution between urban and peripheral areas directly affects accessibility.

Finally, a limitation of this study is that it does not fully account for the edge effect, which is a common drawback of the E2SFCA method. The edge effect refers to a distortion or bias in accessibility scores, which occurs near the boundaries of the study area. In reality, residents near the borders of Asan may utilize medical resources from neighboring regions. However, our study data is only within Asan's administrative boundary because the use and incorporation of cross-boundary data is restricted. As a result, future research should consider an expanded approach incorporating road networks and medical resource data from adjacent areas when available. Then, sensitivity analyses should be conducted to estimate the impact of these omitted areas.

In addition, this study was based on data from a single time point and did not account for temporal variations in medical resources and networks. Thus, the analysis may fail to capture temporal dynamics in healthcare access, such as seasonal variations in service usage or long-term trends in spatial equity. To address this, future studies incorporating multitemporal data can enable dynamic assessments of healthcare accessibility, thereby providing deeper insights through temporal variations.

To conclude, we analyzed the healthcare accessibility in Asan, Chungcheongnam-do, by the E2SFCA method at the node level of the road network. Utilizing the Gini coefficient (a global inequality index), we identified the overall disparities in healthcare accessibility within Asan. Community detection and a hotspot analysis further revealed significant differences in accessibility between urban and peripheral areas. This verified that medical resources are concentrated in urban centers whereas accessibility remains insufficient in peripheral regions.

These findings provide a detailed understanding of the healthcare accessibility disparities in specific areas of Asan. Additionally, the need for policy interventions to improve the distribution of medical resources and accessibility is emphasized. In particular, improving the healthcare accessibility in peripheral areas requires additional medical resource allocation and infrastructure enhancements. This study has provided an important foundational resource for regional healthcare policy planning in Asan. Moreover, the road-network-based accessibility assessment method can serve as an effective reference for similar studies and policy decisions.

Acknowledgments

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