Local healthcare resources associated with unmet healthcare needs in South Korea: a spatial analysis

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Abstract

Despite national initiatives to enhance healthcare accessibility, unmet healthcare needs in South Korea remain notably high, particularly in specific regions. This study investigated the factors contributing to geographical disparities in unmet healthcare needs by employing spatial regression models to examine the spatial interactions between healthcare resources and unmet needs. Utilizing data from the 2020 Community Health Survey and Statistics Korea for 216 local government entities, excluding remote areas to ensure data consistency, we identified significant spatial clusters of unmet healthcare needs. These clusters are primarily located in non-metropolitan regions facing transportation barriers and limited healthcare infrastructure. Spatial regression analysis revealed that general hospitals and clinics are significantly associated with reduced unmet healthcare needs underscoring their critical role in mitigating regional disparities. In contrast, hospitals (≥30 beds) and convalescent hospitals did not exhibit significant effects, likely owing to their focus on specialised inpatient and long-term care services, which do not directly address immediate outpatient needs. These findings advance the understanding of how healthcare resource distribution impacts unmet needs at a regional level in South Korea and highlight the necessity for allocating general hospitals and clinics strategically to promote health equity. Based on these results, we recommend evidence-based policy interventions that optimise existing healthcare resources and strategically deploy new facilities in underserved regions. These insights provide valuable guidance for policymakers to reduce geographical health disparities and enhance overall public health outcomes.

Introduction

Ensuring equitable access to medical services is a fundamental objective of public health policy (Le Grand, 1982). This entails providing equal opportunities for individuals to obtain necessary healthcare services regardless of their socioeconomic status or geographic location (Mooney *et al.*, 1991). In 2017, South Korea expanded its Health Insurance Coverage policy to achieve this goal, incorporating over 3,800 previously excluded medical services and materials. This policy was designed to alleviate the financial burden of medical expenses for vulnerable populations by covering high-demand, previously uninsured items (Kim, 2018). Despite these efforts, the rate of unmet healthcare needs in South Korea remained high in 2018 (12.2%), compared to 8.3% in the United States (Centers for Disease Control and Prevention

(CDC), 2018; Joo *et al.,* 2022). Unmet healthcare needs refer to situations in which individuals recognise the necessity of medical services but cannot access them promptly (Aday & Andersen, 1974). This issue violates the fundamental right to health, leading to delayed diagnoses and treatments, deteriorated health outcomes and increased mortality rates (Tidikis & Strasen, 1994; Alonso *et al.*, 1997; Braveman & Gruskin, 2003). Additionally, it can escalate overall healthcare costs because of the need for potentially more extensive or expensive treatments at a later date (Allin *et al.*, 2010). The causes of unmet healthcare needs are primarily categorised as availability, accessibility and acceptability (Penchansky & Thomas, 1981; Chen & Hou, 2002; Nelson & Park, 2006; Sibley & Glazier, 2009). Availability refers to the adequacy and distribution of healthcare resources, such as facilities and service waiting times, which are influenced by the geographical distribution of medical resources (Pyle & Lauer, 1975). Accessibility involves financial capability, distance to healthcare facilities, travel time and transportation infrastructure (Shin & Lee, 2011), while acceptability is determined by the individual's perceptions and cultural attitudes towards healthcare (Penchansky & Thomas, 1981). The COVID-19 pandemic has further underscored the importance of community healthcare systems and the effective distribution of healthcare resources to enhance accessibility (Raeesi *et al.*, 2022; Yun *et al.*, 2022).

Despite governmental initiatives such as the Medically Underserved Area programme and support for central healthcare institutions, disparities in healthcare accessibility persist, particularly among vulnerable populations in non-metropolitan regions (Yun *et al.*, 2021; Yim, 2022). In particular, South Korea's pronounced urban-rural development disparities and the rapid increase in its ageing population intensify these healthcare challenges suggesting that unmet healthcare needs are likely to escalate (Ji *et al.*, 2024). Individual health is influenced by personal factors and community-level determinants, including geographic conditions, population distribution, transportation infrastructure and proximity to healthcare facilities (Diez-Roux, 1998; Shin & Lee, 2011). Social relationships centred around residential areas further highlight the importance of considering contextual healthcare resources in policies aimed at improving health status and quality of life (Rho & Kwak, 2005). Moreover, existing research presents conflicting findings regarding the association between local healthcare resources and unmet healthcare needs. While Litaker and Love (2005) and Peterson and Litaker (2010) found no significant correlation, Heo *et al.* (2012) reported a positive association. Although other studies have examined healthcare resource imbalances and spatial perspectives, they have not thoroughly explored the factors influencing geographical disparities in unmet healthcare needs across different medical institutions (Kim & Jeong, 2010; Kitchen *et al.*, 2011; Jeon *et al.*, 2012).

This study aimed to address these gaps by employing spatial regression models to analyse the spatial distribution of unmet healthcare needs in South Korea and investigate how different medical institutions contribute to geographical disparities. Focusing on the spatial interactions between healthcare resources and unmet needs, this research wished to provide actionable insights into healthcare resource allocation and advance understanding of health equity in regional contexts.

Materials and Methods

Study area

The geographic scope of this study encompassed South Korea's administrative divisions comprising nine metropolitan cities (Seoul, Busan, Daegu, Incheon, Gwangju, Daejeon, Sejong, Ulsan and Jeju) and corresponding provinces. The analysis units were defined at the city, county and district levels (si/gun/gu), totalling 226 local government entities as of 2020. For this spatial analysis, 216 regions were included, excluding islands and remote areas owing to data limitations and ensuring uniformity in regional data.

Variables

Dependent variable

Unmet healthcare needs were measured using data from the 2020 Community Health Survey. Individuals aged ≥65 years, who responded 'yes' to the question 'During the past year, have you ever been unable to go to a hospital or clinic (dentist not including) when you wanted to?' and identified 'inconvenient transportation or long distance' as the main reason, were considered to have unmet healthcare needs (Shin *et al.*, 2014). This criterion focused on accessibility barriers related to geographical and transportation factors acknowledging that other factors, such as financial constraints or cultural attitudes, may also contribute to unmet needs but these relationships are beyond the scope of this analysis.

Independent variables

Private medical institutions in Korea are classified into four main categories: hospitals with ≥ 30 beds, convalescent hospitals, general hospitals and clinics. Hospitals are medical facilities with a bed capacity of ≥30, primarily catering to in-patients requiring hospitalisation for various treatments. Convalescent hospitals have a bed capacity of ≥30 and primarily offer medical services and long-term care for older individuals or patients requiring extended care and rehabilitation. General hospitals have a capacity of ≥100 beds and operate at least seven medical specialties; those with ≥300 beds must provide services for at least nine medical specialties. Clinics are medical facilities with fewer than 30 beds that provide primary healthcare services to residents, such as general consultations, basic medical treatments, preventive care, health education and minor procedures. Clinics serve as the first point of contact in the healthcare system and they address common illnesses, chronic conditions, routine health screenings and vaccinations. They play a crucial role in providing accessible healthcare for communities. Table 1 presents the relevant variable definitions.

The analysis methods used

This cross-sectional study aimed to identify factors associated with geographical disparities in unmet healthcare needs at the regional level. As all variables in this study were based on regional data, spatial regression analyses were performed to explore these relationships (Figure 1). Statistical analyses were performed using R Studio (version 2024.04.2) and Geoda software (version 1.20.0.10) programs, while QGIS (version 3.24.1) was used to visualise spatial patterns.

Ordinary least squares (OLS)

We conducted OLS regression analysis to determine the relationship between unmet healthcare needs and the independent variables. Before performing the regression, we verified the presence of multicollinearity among the independent variables. Multicollinearity can lead to imprecise estimation of regression coefficients, adversely affecting the model's reliability (Hutcheson, 2011). We assessed multicollinearity using the Variance Inflation Factor (VIF), where values below 10 indicate no significant multicollinearity issues. In our analysis, all VIF values were below 5, confirming that multicollinearity was not a concern.

Spatial autocorrelation

Spatial autocorrelation describes the correlation of a variable with itself through space, indicating that spatial data points are not independent (Anselin & Bera, 1998). We calculated Moran's *I* statistic (Moran, 1950) to assess whether unmet healthcare needs exhibited spatial clustering. A significant Moran's *I* suggests that similar values of unmet healthcare needs (high or low) are geographically clustered rather than randomly distributed across the study area. Spatial data refers to the interdependence and interaction between geographical spaces with similar characteristics. These spaces are spatially adjacent and tend to be highly correlated (Anselin & Bera, 1998). Apart from this global assessment, Local Indicators of Spatial Association (LISA) identify clusters or 'hotspots' within the study area (Anselin *et al.*, 2002). By employing Moran's *I* and LISA analyses, this study identified significant spatial patterns and clusters of unmet healthcare needs across the study area.

Univariate spatial autocorrelation

Moran's *I* statistic was employed to analyse univariate spatial autocorrelation and assess the spatial distribution of unmet healthcare needs, while LISA was used for local assessments. Results of the former range from −1 (perfect dispersion) to +1 (perfect clustering), with values near zero suggesting a random spatial pattern, and those of the latter classify spatial patterns into four categories: High-High (HH), High-Low (HL), Low-High (LH), And Low-Low (LL). HH regions represent clusters where the area and its neighbours exhibit high unmet healthcare needs, signalling areas with concentrated disparities. HL regions indicate areas with high unmet needs surrounded by neighbours with relatively low unmet needs, suggesting potential outliers. Conversely, LH regions denote areas with low unmet needs adjacent to neighbours with high unmet needs, whereas LL regions signify clusters where the area and its neighbours have low unmet healthcare needs, reflecting areas of relative advantage.

Bivariate spatial autocorrelation

We also employed bivariate Moran's *I* statistic (Anselin *et al.*, 2002), which examines the spatial correlation between one variable at a location and another at neighbouring locations and can thus reveal spatial association patterns between different attributes the spatial relationship between unmet healthcare needs and resources. Specifically, bivariate Moran's *I* enables the identification of whether regions with high unmet healthcare needs are spatially correlated with low densities of medical institutions or vice versa. This study also explored the spatial lag and the spatial error models – two commonly used spatial regression models – to analyse the data with spatial autocorrelation, address geographical issues and enhance results' reliability.

Spatial lag model (SLM)

This approach assumes that spatial autocorrelation is inherent in the dependent variable. It introduces a spatial weight matrix into the regression equation to account for spatial autocorrelation and eliminates the errors caused by autocorrelation in the regression analysis (Ward & Gleditsch, 2018). The equation for the SLM is as follows:

$$Y_i = \rho W_i Y_j + \beta X_i + \varepsilon_i \quad \text{(Eq.1)}$$

where Y_i and Y_j represent the dependent variables at locations *i* and

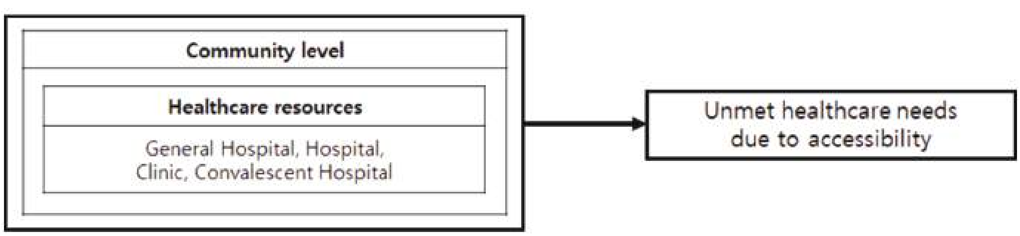

Figure 1. Conceptual framework of the research model.

Table 1. Definitions of study variables.

Variable		Definition	Source
Independent	Unmet healthcare needs	Percentage of individuals aged ≥65 years reporting an inability to visit a hospital or clinic (excluding dentists) due to transportation or distance barriers	Community Health Survey (2020)
Dependent	General hospital	Medical institution with ≥100 beds, providing specialized services across multiple medical fields	
	Hospital	Medical institution with ≥30 beds, primarily offering inpatient and outpatient care	Korean Statistical Information Service (2020)
	Clinic	Medical institution with <30 beds, delivering outpatient care and preventive services	
	Convalescent hospital	Healthcare facility capable of accommodating ≥30 long-term care patients and providing medical services	

j, respectively; X_i the independent variables in region i; r is the spatial regression coefficient of the SLM; W_i the spatial weight matrix of region i; b the regression coefficient; and ε_i the error term for region i. The term W_iY_i is the spatial lag that explains the spatial autocorrelation in the dependent variable.

Spatial error model (SEM)

Contrary to the SLM, the SEM assumes a geographical dependency in the error term of the OLS regression equation. By adding a spatial weight matrix, the SEM accounts for potential spatial autocorrelation in the residuals, ensuring no spatial autocorrelation in the error term (Ward & Gleditsch, 2018). The equation for the SEM is as follows:

$$Y_i = \beta 0 + X_i\beta + \lambda W_i\xi_i + \varepsilon_i \qquad \text{(Eq.2)}$$

where Y_i represents the dependent variable in region i; X_i the independent variables in region i, β the regression coefficient; W the spatial weight matrix; ξ_i the spatial error term for region i; λ the degree of correlation among these geographical components; and ε_i the non-spatially correlated error term (Ward & Gleditsch, 2018; Mollalo et al., 2020).

Spatial dependence tests and model fit evaluation

The choice between the spatial lag and spatial error models was guided by the robust Lagrange multiplier (LM) test (Anselin, 2001), which determines whether residual spatial dependence primarily affects the dependent variable (lag) or error term (error). When both LM (lag) and LM (error) were statistically significant, the model with the lower LM statistic was selected, indicating a diminished degree of unaccounted spatial autocorrelation. Model fit was subsequently assessed using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), where lower values signified more parsimonious and better-fitting solutions (Vrieze, 2012). The coefficient of determination (R^2) was also examined to gauge the explanatory power of each model, with higher R^2 values suggesting stronger congruence between predicted and observed outcomes. Additional diagnostic procedures included the Jarque-Bera test to confirm residual normality, along with the Breusch-Pagan and Koenker tests to evaluate potential heteroskedasticity (Rossi *et al.*, 2020).

Results

Descriptive statistics

Table 2 presents the descriptive statistics of the study variables. The average geographical disparity rate of unmet healthcare needs was 0.46%, with a range from 0% to 3.5%. The mean number of general hospitals, hospitals, convalescent hospitals and clinics per region was 1.4 (ranging from 0 to 11), 6.8 (ranging from 0 to 41), 7.1 (ranging from 0 to 40), and 148 (ranging from 1 to 1,700), respectively. Notably, the clinics exhibited the highest inter-regional variability. Choropleth maps in Appendix 1 represent the spatial distributions of these variables visually.

Regions with high unmet healthcare needs

Table 3 lists the ten regions with the highest percentages of unmet healthcare needs. The top ten regions were found to be distributed across the study area: Gyeongsangbuk-do (four regions), Gyeongsangnam-do (one region), Jeollanam-do (two regions), Jeollabuk-do (one region), Gyeonggi-do (one region) and

Table 2. Descriptive statistics of the variables.

Variable	Study area	Mean	SD	Minimum	Maximum
Unmet healthcare needs	216	0.46	0.61	0	3.5
General hospital	216	1.4	1.7	0	11
Hospital	216	6.8	7.4	0	41
Clinic	216	148	183	1	1,700
Convalescent hospital	216	7.1	7	0	40

SD, standard deviation.

Table 3. Top 10 regions with the highest unmet healthcare needs.

No.	Study area (si-gun-gu)	Unmet healthcare needs (%)
1	Bonghwa-gun, Gyeongsangbuk-do	3.50
2	Gokseong-gun, Jeollanam-do	3.08
3	Yeoncheon-gun, Gyeonggi-do	3.02
4	Uiseong-gun, Gyeongsangbuk-do	2.92
5	Tongyeong-si, Gyeongsangnam-do	2.44
6	Goseong-gun, Gangwon-do	2.02
7	Yeongcheon-si, Gyeongsangbuk-do	2.01
8	Cheongsong-gun, Gyeongsangbuk-do	1.83
9	Gurye-gun, Jeollanam-do	1.82
10	Jinan-gun, Jeollabuk-do	1.72

Gangwon-do (one region), with Bonghwa-gun, Gyeongsangbuk-do having the highest rate at 3.5%.

Univariate spatial autocorrelation

Moran's *I*, calculated to assess the spatial autocorrelation of unmet healthcare needs, revealed a significant positive spatial autocorrelation (0.235, $p<0.001$), indicating that regions with similar unmet healthcare needs are geographically clustered. HH clusters were identified in Gangwon-do (Samcheok-si, Taebaek-si), Gyeongsangbuk-do (Yeongyang-gun, Andong-si), Jeollabuk-do (Jinan-gun) and Jeollanam-do (Gurye-gun). LL clusters were predominantly located in metropolitan areas such as Seoul and Gyeonggi-do (Figure 2). These findings provide critical insights into the geographical disparities in healthcare access and utilisation, highlighting areas that may require targeted interventions to address unmet needs effectively.

Bivariate spatial autocorrelation

The examination of the spatial correlation between unmet healthcare needs and each type of healthcare resource can be seen in Figure 3. The results, presented in Table 4, show significant negative spatial correlations between unmet healthcare needs and the number of general hospitals (−0.144), hospitals (−0.202), clinics (−0.282) and convalescent hospitals (−0.16). Not surprisingly, it was found that regions with more healthcare institutions tend to have lower unmet healthcare needs. However, these findings elucidate the spatial dependencies and interactions between healthcare resource distribution and unmet needs, informing more precise and targeted policy interventions.

Spatial dependence tests

Table 5 displays the results of the Lagrange multiplier (LM) tests for spatial dependence. The LM (lag) and LM (error) coefficients were statistically significant (lag: 7.4178; error: 6.7821) indicating the presence of spatial dependence in the dependent variable and error term.

Ordinary least squares regression (OLS)

This regression model, detailed in Table 6, yielded an R^2 value of 18.3%, suggesting that the independent variables explain approximately 18.3% of the variance in unmet healthcare needs. The coefficients for the number of general hospitals (−0.064, $p<0.05$) and clinics (−0.001, $p<0.01$) were significantly associated with reduced unmet healthcare needs. The variables hospital and convalescent hospital were not statistically significant.

Spatial lag model (SLM)

Here the R^2 was 22.8% indicating enhanced explanatory power compared to the OLS model. The spatial autocorrelation coefficient (ρ) was 0.228 ($p<0.01$). Similar to the OLS results, the coefficients for the number of general hospitals (−0.0646, $p<0.05$) and clinics (−0.0007, $p<0.1$) were significantly negatively associated with unmet healthcare needs. Hospitals and convalescent hospitals remained non-significant.

Spatial error model

Here the R^2 was 20.6%. The spatial error coefficient (λ) was 0.206 ($p<0.05$). In this model, the coefficients for the number of general hospitals −0.061, $p<0.1$) and clinics (−0.0007, $p<0.1$)

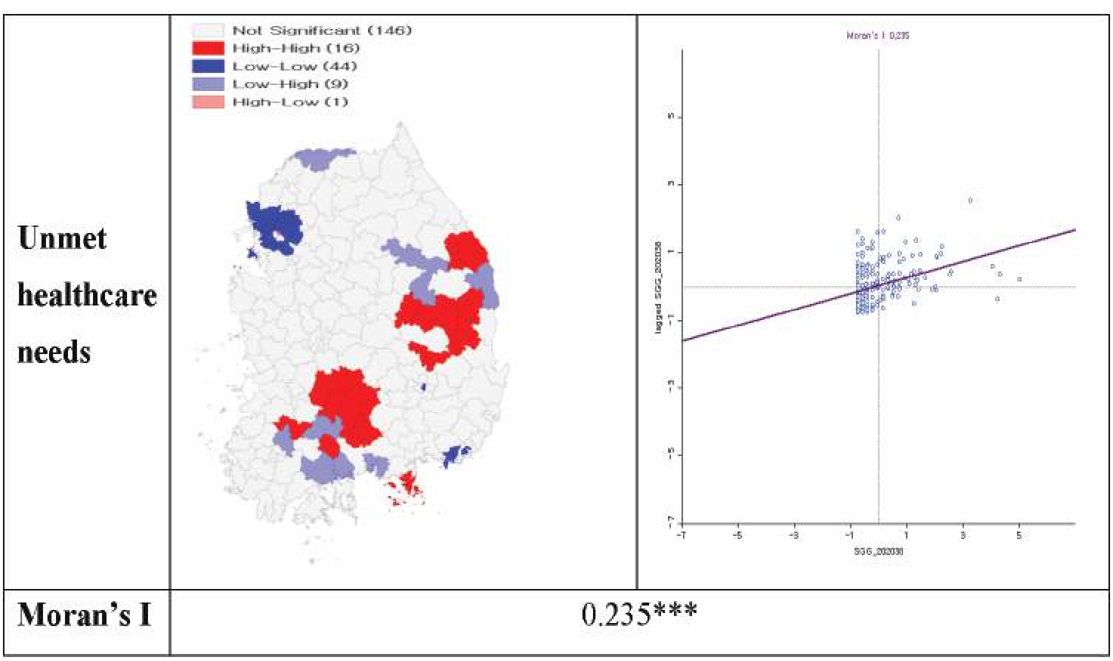

Figure 2. Spatial autocorrelation of the unmet healthcare needs. ***p< 0.001, **p< 0.01, *p<0.1

were negatively associated with unmet healthcare needs, albeit with marginal significance. Hospitals and convalescent hospitals remained non-significant.

Model fit evaluation

Table 6 compares the fit of the OLS, SLM, and SEM models. The SLM exhibited the highest R^2 (22.8%) and the lowest Akaike Information Criterion (AIC) value (356.093), followed by the SEM (R^2= 20.6%, AIC = 359.16) and OLS (R^2= 18.3%, AIC = 363.235). Thus, the SLM was identified as the most suitable model for this analysis based on these criteria.

Discussion

This study examined geographical disparities in unmet healthcare needs across 216 municipalities in South Korea using spatial analysis. Our findings reveal significant spatial clustering of unmet

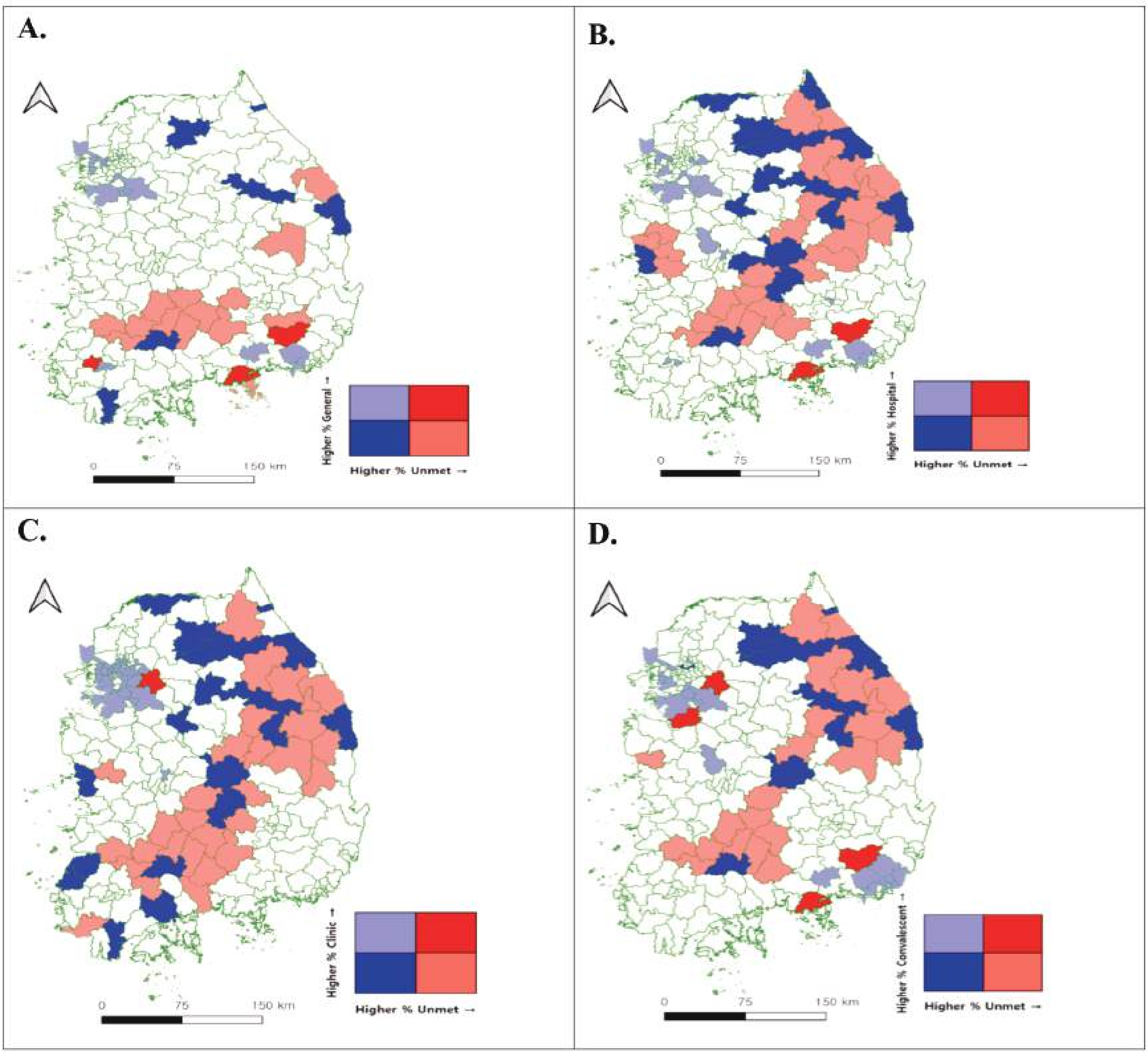

Figure 3. Bivariate LISA cluster maps of the distribution of unmet healthcare needs and healthcare resources showing their spatial relationships. **A**) General hospital; **B**) Hospital; **C**) Clinic; **D**) Convalescent hospital.

Table 4. Results of bivariate Moran's I analysis.

	General hospital	Hospital	Clinic	Convalescent hospital
Unmet healthcare needs	-0.144	-0.202	-0.282	-0.16

healthcare needs, particularly in non-metropolitan regions facing transportation challenges and limited healthcare resources. They corroborate previous studies that emphasise the influence of geographic factors on healthcare utilisation disparities (An *et al.*, 2014; Kim *et al.*, 2021). Specifically, the vulnerable areas identified, constrained healthcare resources and inadequate transportation infrastructure hinder access to medical services compared to their urban counterparts, leading to significant disparities in health outcomes (An *et al.*, 2014; Raeesi *et al.*, 2023). Therefore, enhancing healthcare infrastructure and accessibility in these vulnerable areas is essential.

Our spatial regression analysis demonstrated that the presence of general hospitals and clinics significantly reduces unmet healthcare needs. This underscores the critical role these institutions play in mitigating regional disparities and supports the notion that increasing the availability of comprehensive medical facilities and primary care services enhances healthcare accessibility (Oliver & Mossialos, 2004; Perucca *et al.*, 2019). In contrast, hospitals and convalescent hospitals did not show significant effects on reducing unmet healthcare needs. This may be attributed to their specialised focus on inpatient care and long-term treatment, which do not directly address the immediate outpatient needs captured in our study. Data limitations or the specific services offered by these facilities could also contribute to this result. Future research incorporating individual-level data and mixed-method approaches could provide a deeper insight into these findings.

The model comparison indicated that the SLM was the most suitable, emphasising the importance of considering spatial dependence in studies of healthcare resource allocation. The SLM analysis revealed that increasing the number of general hospitals and clinics in a region benefits that specific area and generates positive spill-over effects in neighbouring regions, thereby enhancing overall healthcare service utilisation. Understanding these spatial dynamics is crucial for developing regional health equity policies (Park, 2012).

Policy implications

Evidence-based policy interventions that strategically allocate healthcare resources is recommended—particularly general hospitals and clinics—to underserved regions. Enhancing healthcare infrastructure in the identified vulnerable areas, such as certain regions of Gyeongsangnam-do, Gwangju, and Gyeonggi-do, can reduce geographical health disparities. This approach is consistent with the UK 'spearhead areas' strategy, which has successfully reduced health disparities through targeted investments (Department of Health, 2010; Shin & Lee, 2011). Reallocating healthcare personnel and facilities based on actual demand, rather than simply increasing the number of medical institutions, can ensure high-quality services and address regional imbalances more effectively (National Health Service, 2015). Moreover, policies should focus on improving transportation infrastructure and accessibility to healthcare services in non-metropolitan regions (Mohammadi *et al.*, 2021). Policymakers can more effectively address the disparities highlighted in this study by linking the identified impact of clinics and general hospitals on reducing unmet needs to specific strategies—such as enhancing primary care services and expanding comprehensive hospital facilities. Implementing these recommendations can lead to more equitable healthcare access, reduce regional disparities, and improve public health outcomes.

Strengths and limitations

This study has several limitations that should be addressed in future research. First, because of data constraints, the ecological design did not account for individual-level factors such as personal health behaviours, socioeconomic status, or cultural attitudes towards healthcare (Schwartz, 1994). These individual factors can significantly influence healthcare utilisation and unmet needs. Future research should incorporate individual-level data for a more

Table 5. Lagrange multiplier (LM) test for spatial dependence.

Lagrange multiplier (lag)	df = 1	7.4178**
Lagrange multiplier (error)	df = 1	6.7821**

***p<0.001, **p<0.01, *p<0.1.

Table 6. Comparison of estimation results across OLS, SLM and SEM models.

Model variables		OLS			SLM			SEM		VIF
	Coef.	SD	Z	Coef.	SD	Z	Coef.	SD	Z	
Constant	0.726***	0.0557	13.039	0.5613***	0.0704	7.971	0.6821***	0.0629	10.847	
General hospital	-0.064*	0.0323	-1.974	-0.0646*	0.0311	-2.079	-0.061*	0.0316	-1.934	2.1
Hospital	0.012	0.0113	1.042	0.0099	0.0108	0.922	0.0093	0.0111	0.841	4.9
Clinic	-0.001**	0.0003	-3.123	-0.0007*	0.0003	-2.309	-0.0007	0.0003	-2.119	2.5
Convalescent hospital	-0.014	0.0087	-1.661	-0.0134	0.0083	-1.602	-0.0136	0.0086	-1.585	2.6
Rho (lambda)				0.264**	0.224*					
R^2	0.183042			0.227983			0.206385			
Log-likelihood	-176.617			-172.047			-174.58			
AIC	363.235			356.093			359.16			
Schwarz criterion	380.111			376.345			376.037			
Jarque-Bera	517.1797***									
Breusch-Pagan test	5.3357			7.0969			7.5573			
Koenker-Bassett test	1.2975									
Likelihood ratio test				9.1415***			4.0746**			

***p<0.001, **p<0.01, *p<0.1 OLS, ordinary least squares), SLM, spatial lag model), SEM, variance inflation factor, SD, standard deviation, AIC, Akaike Information cxriterion.

comprehensive understanding of the factors influencing unmet healthcare needs. Mixed-method approaches, including qualitative studies, could also explore personal experiences and perceptions that quantitative data may not capture. Second, the study's cross-sectional nature limits the ability to infer causality between healthcare resources and unmet needs. The temporal sequence of events remains unclear, and the observed associations may not reflect causal relationships. Longitudinal studies are needed to examine temporal dynamics and establish causality more effectively. Third, some regions were excluded from the analysis owing to their island or remote locations, and certain regions were combined or modified to ensure uniformity in regional data. This exclusion may affect the findings' generalizability. Furthermore, geographic data differ from general data because spatial units are not independent and exhibit spatial dependence or autocorrelation, relating to the modifiable areal unit problem (MAUP) (Cho, 2010). For example, the choice of administrative boundaries at the si/gun/gu level may influence the results, potentially masking local variations within regions and leading to underestimation or overestimation of spatial relationships. Future studies could explore different spatial scales, such as smaller administrative units, and employ sensitivity analyses to assess the impact of MAUP on the findings. Finally, the lack of significant effects of hospitals and convalescent hospitals warrants further investigation. Specific contextual factors, such as service types, patient populations served, or regional healthcare policies, may influence these results. Data limitations regarding detailed hospital characteristics could have affected the analysis. Future research using more granular data on healthcare facilities and incorporating variables such as service scope, patient demographics, and operational efficiency could provide deeper insights.

Despite these limitations, this study makes several important contributions to understanding geographical disparities in unmet healthcare needs. By employing spatial regression models that account for spatial interactions, this study provides a more nuanced analysis than previous research that assumed uniform effects across regions. The detailed examination of the direct and indirect effects of healthcare facility distribution on unmet needs underscores the necessity of considering spatial distribution in healthcare resource allocation to enhance service quality and equity in healthcare utilisation. Furthermore, identifying specific municipalities with high unmet healthcare needs offers valuable information for targeted policy interventions and resource allocation (Dong *et al.*, 2023). The study's findings provide actionable insights for policymakers aiming to manage healthcare disparities, emphasising the importance of incorporating spatial analysis into public health policy to guide tailored resource allocation strategies that address individual accessibility and broader social and structural influences. Additionally, this study advances spatial epidemiology methodologies by integrating spatial autocorrelation analyses with regression models, offering a robust framework for future research in similar contexts. These methodological advancements contribute to the broader discourse on health equity and equitable resource allocation, making this study a significant addition to public health and healthcare policy.

Conclusions

This study significantly contributes to understanding geographical disparities in unmet healthcare needs within South Korea by leveraging community-level data and advanced spatial analysis techniques. By identifying the critical role of general hospitals and clinics in reducing unmet healthcare needs, the research provides actionable insights for policymakers and public health professionals. The findings advocate for strategic, needs-based allocation of healthcare resources and emphasise the importance of empowering local governments through capacity-building, targeted funding, and supportive policy frameworks. Ultimately, this study underscores the necessity of tailored, evidence-based strategies to promote health equity and improve public health outcomes across diverse regions.

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Online supplementary materials
Appendix 1. Choropleth maps of variables