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RESEARCH ARTICLE

SPATIAL ANALYSIS OF HEALTHCARE VULNERABILITY AND ACCESSIBILITY UNDER PMJAY IN UTTAR PRADESH

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ABSTRACT

This study investigates spatial disparities in healthcare access under the Ayushman Bharat Pradhan Mantri Jan Arogya Yojana (PMJAY) across the districts in Uttar Pradesh, India. Despite being the highest contributor to Ayushman card distribution and hospital empanelment under PMJAY, Uttar Pradesh ranks low in the hospital admissions. This reflects a gap between coverage and utilization.

Using district-level data from the District Wise Development Indicators (2021), National Family Health Survey-5 and the PMJAY Dashboard (2024), the study constructed a composite vulnerability index. Spatial analysis techniques, including Local Indicators of Spatial Association (LISA), percentile mapping, and spatial regression models were employed. This paper analyzes district variations in utilization of PMJAY and examines that how the social, economic and health infrastructure of the districts shape the utilization pattern. The results reveal that educational disadvantage, rural location, and infrastructure gaps are significantly associated with lower healthcare utilization.

The Spatial Error Model (SEM) provided the best model fit, indicating that unobserved spatial factors play a critical role in shaping healthcare outcomes. The findings highlight the need for geographically targeted health policies that address structural inequalities to enhance the effectiveness of public health insurance programs like PMJAY.

KEYWORDS

PMJAY, spatial analysis, Uttar Pradesh, health inequality, LISA, spatial regression, healthcare access, vulnerability index

INTRODUCTION

Despite substantial policy commitments to achieving Universal Health Coverage (UHC), India continues to encounter enduring obstacles to equitable healthcare access, particularly in states like Uttar Pradesh (UP), its most populous and socioeconomically diverse state. One of the most significant initiatives toward UHC is the Ayushman Bharat Pradhan Mantri Jan Arogya Yojana (PMJAY), launched in 2018 as the world's largest publicly funded health insurance scheme. PMJAY aims to cover up to ₹5,00,000 ($5520;1 INR=0.011 US $) per family per year for secondary and tertiary healthcare services across empanelled public and private hospitals, eliminating family size caps and enabling nationwide portability [1].

Although the program has scaled up rapidly, with over 500 million Ayushman cards issued nationwide by 2024, substantial regional disparities remain in service utilization. For instance, while states such as Tamil Nadu, Karnataka, and Kerala report high hospitalization rates under PMJAY, Uttar Pradesh despite leading the country in card distribution and hospital empanelment, ranks among low performing states in terms of total admissions [1].

Uttar Pradesh, home to over 240 million people, serves as a critical case study in understanding the spatial inequalities embedded in public health delivery. Despite extensive enrolment (over 52 million Ayushman cards) and a large number of empanelled hospitals (5,867), the utilization of PMJAY services remains skewed, with many vulnerable districts reporting low admissions. Internal disparities between western UP and the underdeveloped eastern and Bundelkhand regions, coupled with rural–urban divides in infrastructure, further exacerbate inequities [2–5].

Various socio-economic determinants such as caste composition, female literacy, pupil–teacher ratio (PTR), electricity access, and income levels intersect to influence healthcare access [6–9]. In particular, education-related vulnerabilities are known to hinder awareness, entitlement navigation, and trust in health systems [10,11]. Furthermore, only a small fraction of private hospitals in aspirational districts offer specialized services, pointing to systemic private sector disengagement[12,13]. Most literature relies on aggregate statistics without uncovering spatial clustering, spatial spillovers, or local drivers of underperformance [14–17].

This study addresses that gap by conducting a district-level spatial analysis of PMJAY implementation in Uttar Pradesh. This study aims to: map the spatial disparities in PMJAY card distribution, hospital empanelment, service utilization across the state, construct multidimensional vulnerability index to identify disadvantaged districts and see the relationship between vulnerability factors and insurance scheme variables. Given the size and demographic complexity of Uttar Pradesh, the results of this study hold broader implications for equitable health policy in India.

DATA AND METHODOLOGY

DATA

The District Wise Development Indicators (DWDI), 2021 and National Family Health Survey (NFHS), 2019-21 are used to calculate the vulnerability index at district level. The indicators related to the PMJAY scheme, including the number of Ayushman Bharat cards distributed, the number of empanelled hospitals, private hospitals, and hospital admissions, were sourced from the PMJAY dashboard (PMJAY - Dashboard) as of June 2024. Due to the unavailability of data pertaining to certain indicators, 71 out of 75 districts of the state were included in the analysis – Hapur, Amethi, Sambhal, and Shamli being excluded.

A composite vulnerability index was considered to provide a holistic measure of socioeconomic disadvantages by aggregating multiple indicators with equal weights. Furthermore, individual vulnerability indicators were also analysed separately to better capture the distinct effects of socioeconomic disparities on healthcare access. The following dimensions were included:

- **Social Vulnerability** is measured by the percentage of SC/ST population, sourced from the District Wise Development Indicators, 2021, as these groups face historical socioeconomic disadvantages[7,8].
- **Economic Vulnerability** is calculated by taking aggregate value of percentage of households belonging to the poorest wealth quintile of a district, using NFHS, 2019-21 data set. Evidence indicates that low-income households are more susceptible to financial shocks [4].
- **Gender Inequality** is calculated using the female literacy rate data, extracted from the DWDI, 2021, as an indicator of gender disparities in education and socioeconomic participation [18].
- **Educational Vulnerability** is captured through the pupil-teacher ratio from the DWDI, 2021, as a high ratio indicates inadequate educational infrastructure and limited access to quality education [6].

- **Rural Status** is measured as the proportion of the rural population in each district, obtained from the DWDI, 2021, since rural areas generally have poorer access to healthcare and bear a higher financial burden of health expenditures [7].
- **Infrastructure Availability** is measured using per capita electricity consumption (K.W.H.), sourced from the DWDI, 2021, as a proxy for overall infrastructural development that influences socioeconomic disparities [19].

Each indicator was scaled[20] using the formula:
$Z_i = (X_i - X_{min}) / (X_{max} - X_{min})$

where Z_i is the normalized value of the indicator, X_i is the actual observed value, and X_{min} and X_{max} are the minimum and maximum values respectively across the districts. The composite vulnerability index was obtained by summing the normalized values of all indicators, with higher scores indicating greater vulnerability[21,22].

This study employs spatial analysis techniques to examine the distribution and accessibility of healthcare services at the district level. The analysis is conducted using GeoDa, a specialized software for spatial econometric modelling and visualization. The primary focus is to identify spatial dependence in key healthcare indicators using Univariate Local Moran's I, which measures the degree of spatial autocorrelation and detects local clustering patterns. A queen contiguity weight matrix was used to define spatial relationships between districts.

Local Indicators of Spatial Association (LISA) analysis was applied to assess spatial clustering and disparities across multiple healthcare-related variables. The LISA analysis was conducted for the Vulnerability Index, Ayushman Card Distribution, Hospital Admissions per One Lakh Ayushman Cards, Total Hospitals per One Lakh Ayushman Cards, Public Hospitals per One Lakh Ayushman Cards and Private Hospitals per One Lakh Ayushman Cards.

For each indicator, a LISA significance map, a cluster map, and a Moran's scatter plot with correlation values were generated. The LISA significance map highlights districts with statistically significant spatial clustering, while the cluster map categorizes districts into four spatial patterns:

- High-High (HH) clusters: Districts with high values surrounded by similar high-value districts.
- Low-High (LH) spatial outliers: Districts with low values surrounded by high-value neighbours.
- Low-Low (LL) clusters: Cold spots with low values surrounded by similar districts.
- High-Low (HL) spatial outliers: High-value districts surrounded by low-value neighbours.

The Moran's scatter plot visually represents the correlation between each district's values and the weighted average of its neighbouring districts. To further analyse spatial disparities, percentile mapping was employed for all indicator variables analysed in LISA. This method was chosen over predefined classification schemes because it offers a data-driven approach, ensuring consistency in comparative spatial representation across different indicators. By using percentiles, we avoid arbitrary thresholds and instead create a uniform distribution-based categorization, which better captures variations in the data and enables more precise spatial comparisons.

Each percentile category was assigned a distinct colour in a red-to-blue gradient to reflect card issuance intensity. Specifically, districts in the >99% were shaded dark red, indicating the highest levels of distribution. The 90%–99% percentile group appeared in orange-red, followed by light orange or tan for the 50%–90% percentile range. Districts within the 10%–50% percentile were coloured light blue, while the 1%–10% percentile appeared in blue, and the <1% percentile was marked with dark blue, indicating the lowest levels of distribution. This color-coded visualization allowed for an intuitive and comparable spatial interpretation of the data.

To better understand the relationship between vulnerability factors and hospital admissions, spatial regression models were employed. Ordinary Least Squares (OLS) regression was first conducted as a baseline model to establish correlations between hospital admissions and independent variables. However, Moran's I test on the residuals confirmed the presence of spatial dependence, necessitating the use of spatial econometric models.

The Spatial Lag Model (SLM) was used to account for spillover effects, where hospital accessibility in one district influences that of neighbouring districts. The model is specified as:

$$Y = \rho WY + X\beta + \epsilon$$

where Y represents hospital admissions, WY is the spatially lagged dependent variable, ρ is the spatial autoregressive coefficient, X is the matrix of explanatory variables, and ϵ is the error term. A significant ρ suggests that hospital admissions in one district are influenced by those in surrounding districts.

Additionally, the Spatial Error Model (SEM) was applied to account for unobserved spatial dependencies that may impact hospital admissions. The model is defined as:

$$Y = X\beta + u, \quad u = \lambda Wu + \epsilon$$

where u represents the spatially autocorrelated error term and λ is the spatial autoregressive parameter for the error term. A significant λ indicates that unobserved spatial factors contribute to hospital admissions.

The dependent variable in this study is hospital admissions per district, representing the extent to which residents utilize healthcare services under the PMJAY scheme. The independent variables included in the model were, number of Ayushman cards distributed, number of empanelled hospitals, economic vulnerability, rural status, infrastructure availability, social vulnerability, gender inequality and education vulnerability. By integrating LISA analysis, percentile mapping, and spatial regression models, this study provides a comprehensive assessment of spatial disparities in hospital accessibility and highlights districts requiring targeted policy interventions.

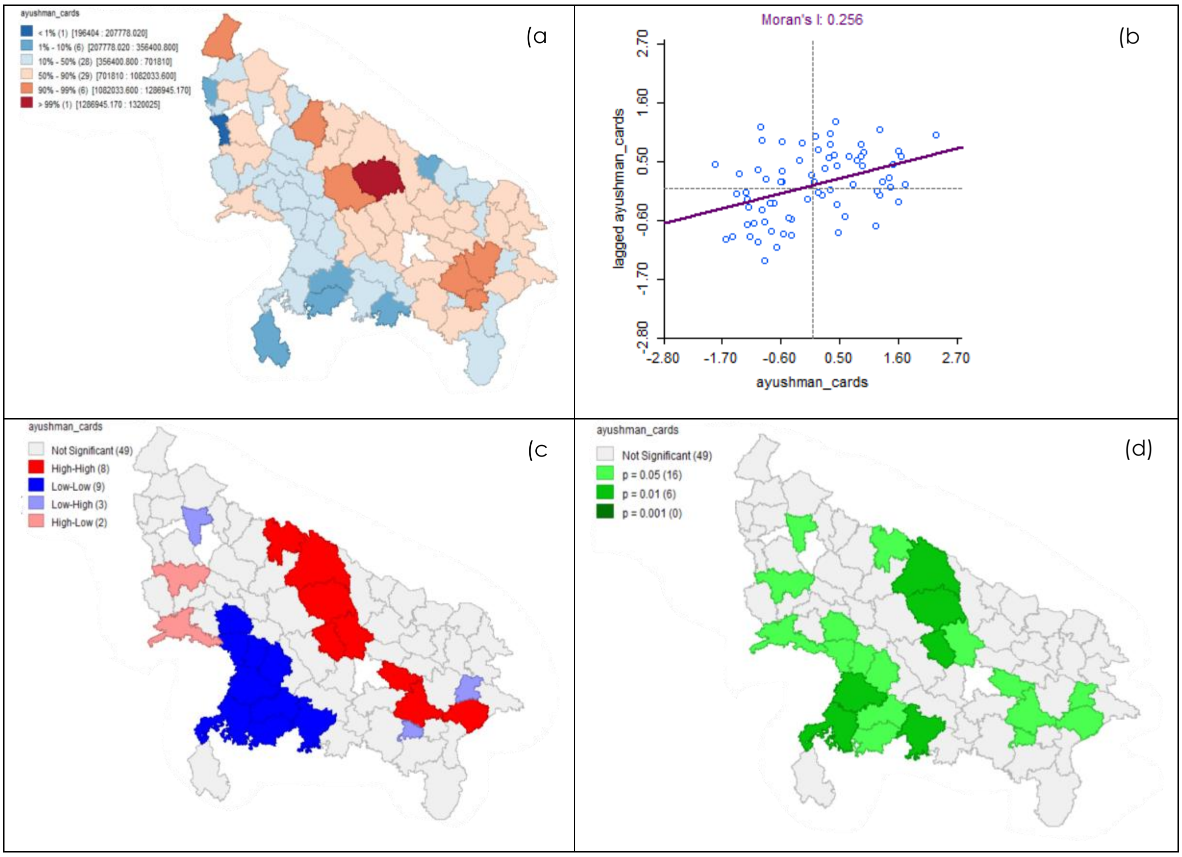
RESULTS

DISTRIBUTION OF AYUSHMAN BHARAT CARD

The distribution of Ayushman Bharat (PMJAY) cards across districts in Uttar Pradesh exhibits significant spatial disparities. A percentile-based classification reveals that Gautam Buddha Nagar falls in the <1% category with only 196,404 cards issued, the lowest in the state (Figure 1). Following this, six districts fall into the 1-10% percentile range such as Lalitput (282,092), Chitrakoot (301,096), Baghpat (353,525), and Shrawasti (319,385). Shrawasti and Chitrakoot were also added in the NITI Ayog's Aspiration districts Program in 2018 advocating for stronger investment in health. On the other end, districts within 90-99% percentile range include Hardoi (1100,411), Bareilly (1086,827), Azamgarh (1140,440), and Jaunpur (1127,444). Sitapur stands in the greater than 99% category, with the highest number of Ayushman cards issued at 1,320,025.

The LISA cluster map revealed high-high clusters (hotspots) in districts such as Pilibhit, Kheri, Sitapur, Barabanki, Jaunpur, Barabanki, Lucknow and Ghazipur, where both the district and its neighbours show high levels of card coverage (Figure 1). These hotspot areas are often highlighted in red in the cluster map. Conversely, low-low clusters (cold spots) were identified in Mainpuri, Etawah, Jalaun, Mahoba, Hamirpur, Jhansi, Kanpur Dehat and Banda, where card distribution is consistently low across adjacent regions. The significance map, based on p-values, confirms that these clusters are statistically meaningful ($p < 0.05$). A Moran's I coefficient of 0.256 indicates moderate positive spatial autocorrelation, suggesting that districts with similar levels of card issuance, whether high or low, tend to be geographically proximate. This clustering implies spatial dependence in PMJAY implementation, highlighting the need for regional strategies to address underperformance in neighbouring low-coverage districts.

FIGURE 1: (A) PERCENTILE PLOT (B)MORAN'S I SCATTER PLOT, (C) UNIVARIATE LOCAL INDICATORS OF SPATIAL ASSOCIATION (LISA) CLUSTER MAP AND, (D) LISA SIGNIFICANCE MAP FOR AYUSHMAN CARDS



STATUS OF HOSPITAL ADMISSIONS PER 1 LAKH AYUSHMAN CARDS

Hospital admissions per one lakh Ayushman cardholders provide a clearer picture of the actual utilization of services under the PMJAY scheme. Substantial inter-district variation is evident across Uttar Pradesh. At the lower end, Chitrakoot reported the lowest hospitalization rate with 2,365.03 admissions, placing it in the less than 1 percentile. In contrast, the highest utilization was recorded in Bareilly, with 13,092.70 admissions per one lakh cards, shown in dark red, placing it in the greater than 99% category. LISA cluster analysis revealed distinct high-high clusters (hotspots) in Amroha, Bulandshahr, Gautam Buddha Nagar, and Rampur, where both the district and surrounding areas exhibit high hospital admissions. The significance map, using p-values, confirmed statistical significance of these clusters ($p < 0.05$), especially across Bundelkhand and southeastern regions of the state. The Moran's I coefficient of 0.336 indicates a moderate positive spatial autocorrelation. This implies that districts with high hospital utilization tend to be located near others with similarly high rates, and vice versa for low-performing districts. These findings suggest persistent underperformance in certain regions points to structural barriers, such as lack of empanelled hospitals, logistical issues, and informational gaps.

REGIONAL DISPARITIES IN VULNERABILITY INDEX

The spatial analysis of the Vulnerability Index across districts in Uttar Pradesh reveals significant regional inequalities. Shrawasti recorded the highest vulnerability score of 4.9. Other highly vulnerable districts in the 90-99% percentile include Kaushambi (4.83), Kheri (4.78), Sitapur (4.79), Bahraich (4.89), Balrampur (4.66), and Sonbhadra (4.83). These districts are largely concentrated in the eastern and central parts of the state, areas historically marked by poor infrastructure and limited economic development. In contrast, the least vulnerable districts include Gautam Buddha Nagar (0.8828), Ghaziabad (1.37), Kanpur Nagar (1.47), Lucknow (1.61), Meerut (1.89) and Varanasi (2.00). These urban and peri-urban districts have greater access to health services, better educational infrastructure, and higher economic activity. The LISA cluster map further supports these findings. High-vulnerability areas in central and eastern UP form tight clusters, emphasizing regional development imbalances. The Moran's I scatter plot shows that highly vulnerable districts are more likely to be located near others with similar levels of vulnerability, reinforcing the presence of spatially structured disadvantage.

FIGURE 2: (A) PERCENTILE PLOT (B)MORAN'S I SCATTER PLOT, (C) UNIVARIATE LOCAL INDICATORS OF SPATIAL ASSOCIATION (LISA) CLUSTER MAP AND, (D) LISA SIGNIFICANCE MAP FOR HOSPITAL ADMISSIONS PER 1 LAKH AYUSHMAN CARDS

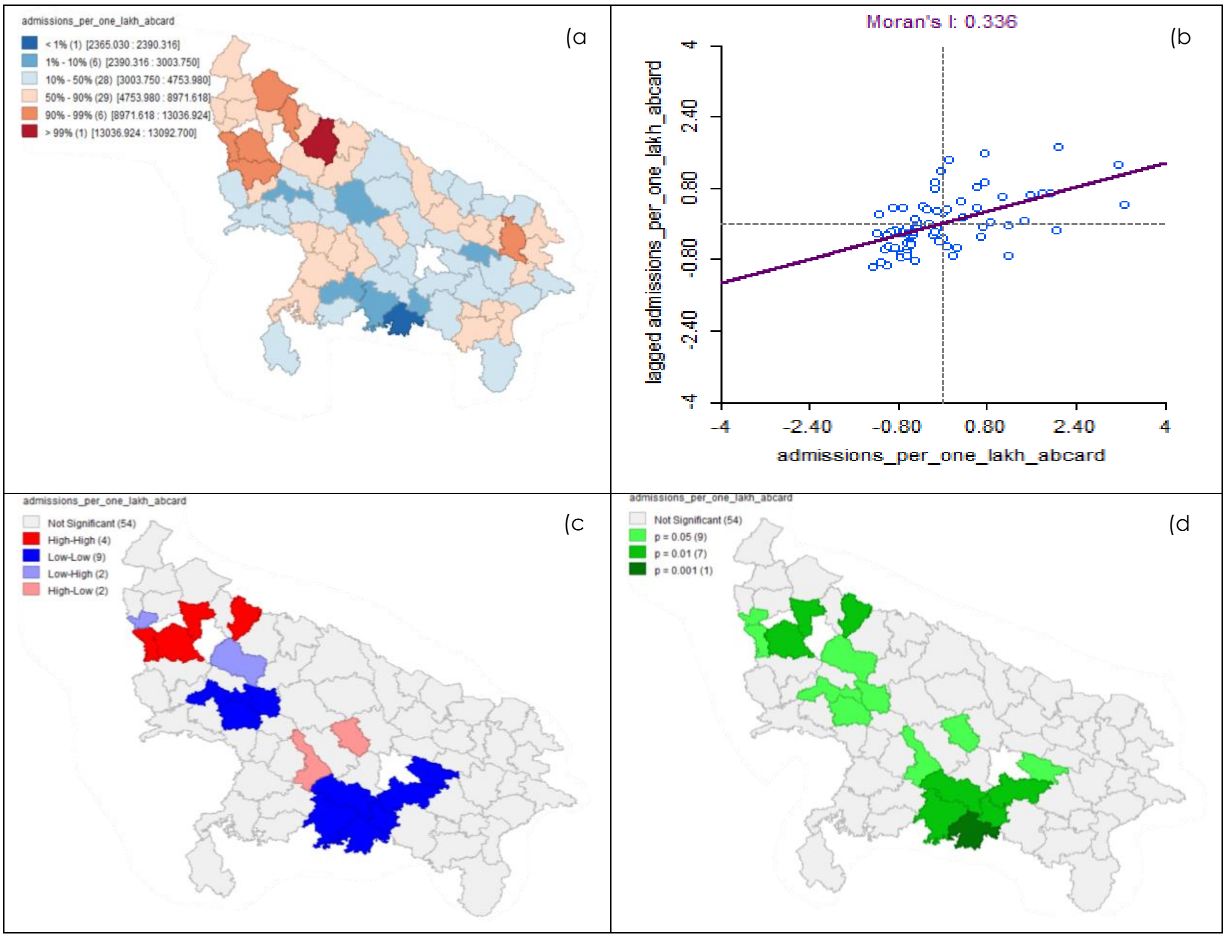
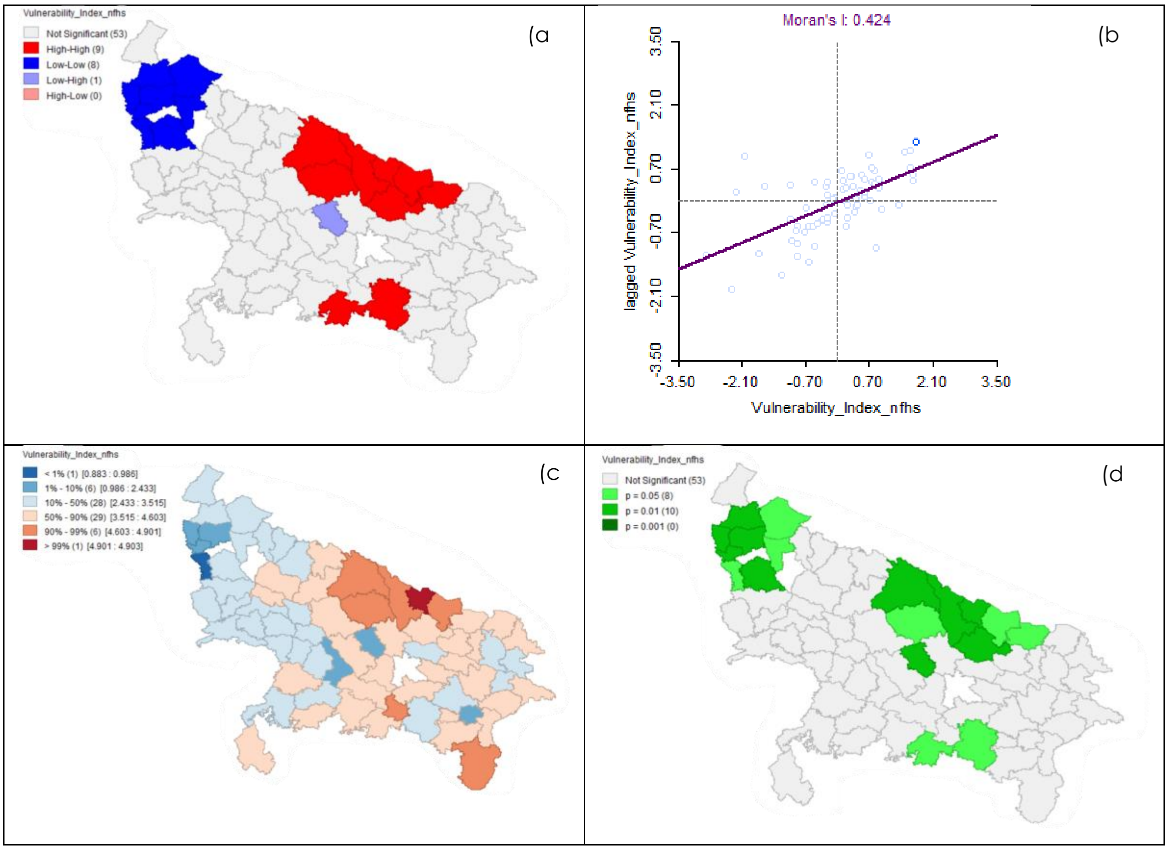


FIGURE 3: (A) PERCENTILE PLOT (B) MORAN'S I SCATTER PLOT, (C) UNIVARIATE LOCAL INDICATORS OF SPATIAL ASSOCIATION (LISA) CLUSTER MAP AND, (D) LISA SIGNIFICANCE MAP FOR VULNERABILITY INDEX

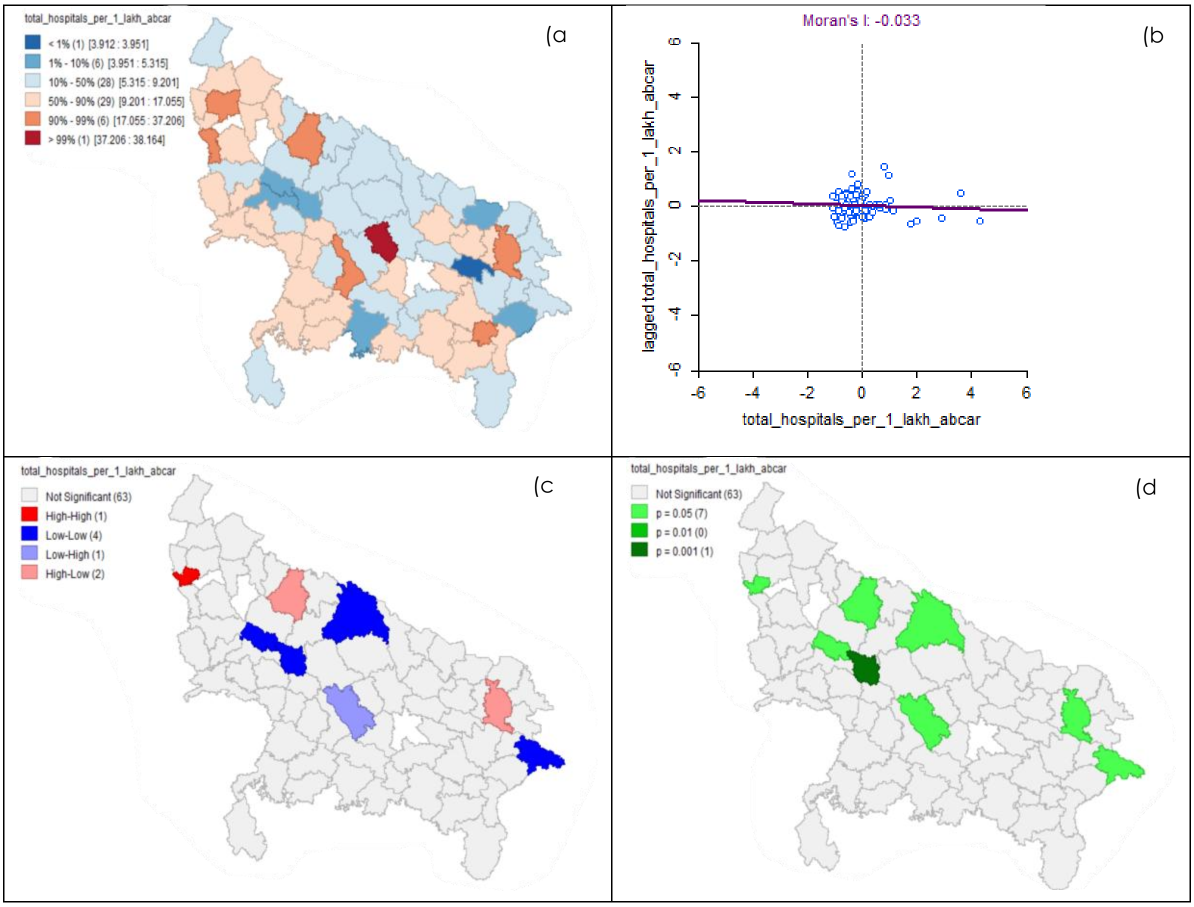


HOSPITAL DENSITY ANALYSIS AND PUBLIC-PRIVATE COMPARISON

Districts such as Lucknow (38.16), Gautam Buddha Nagar (33.60), Kanpur Nagar (29.23), Gorakhpur (23.54), report the highest hospital densities and are shown in dark red on the percentile map. These districts, mostly urban or regional centers, have better access to healthcare facilities and a stronger presence of both public and private providers. On the lower end, districts like Ambedkar Nagar (3.91), Ghazipur (4.09), Etah (4.45), exhibit extremely low hospital densities and are marked in dark blue. This indicates a critical shortage of accessible empanelled hospitals, limiting healthcare service availability.

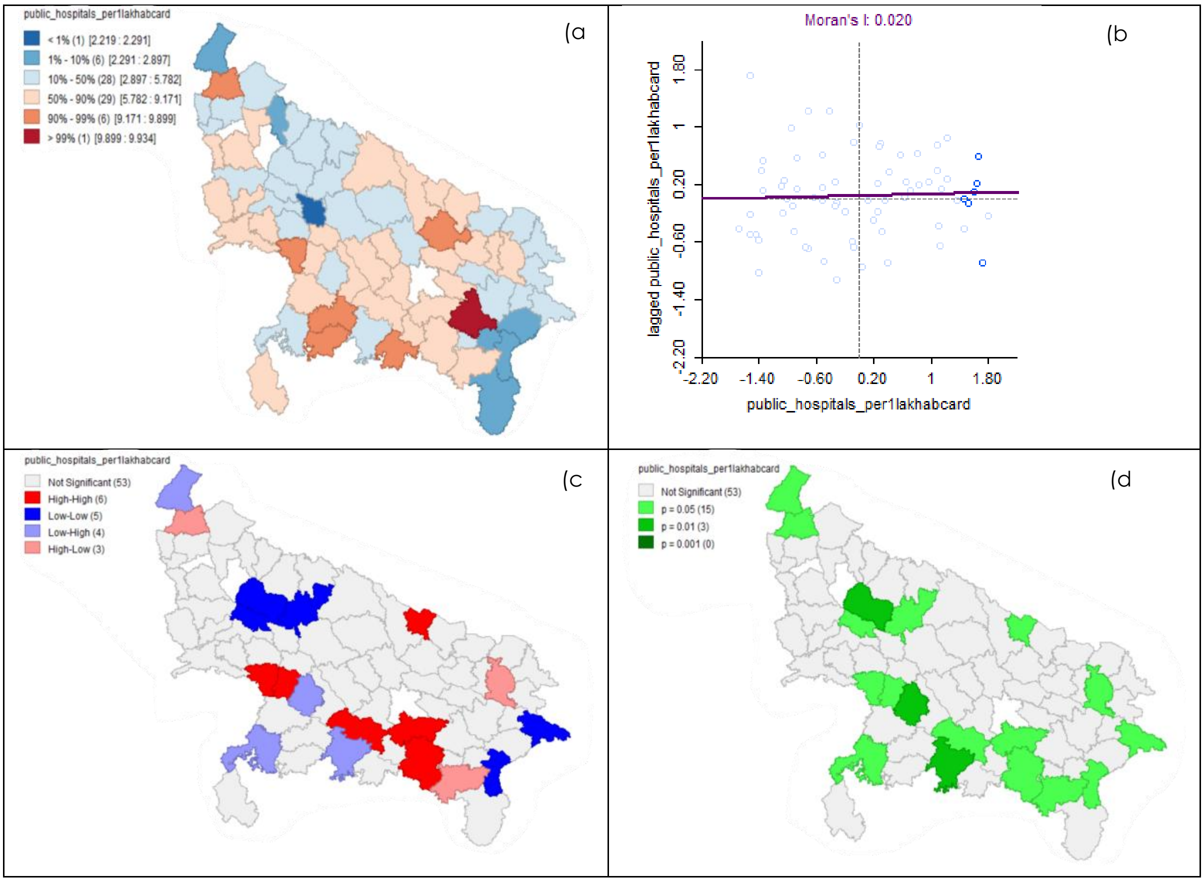
LISA cluster analysis shows that low-low clusters (coldspots) are identified in districts such as Ballia, Farrukhabad, Kasganj, and Kheri, indicating consistently poor hospital access across these neighboring areas. The significance map, with a p-value threshold of 0.05, further validates these clusters, particularly in eastern and central regions. The Moran's I value for total hospital density is -0.033 (Figure 4), suggesting no significant global spatial autocorrelation. This implies that hospital distribution does not follow a clear spatial pattern statewide, possibly reflecting uneven policy implementation or localized infrastructural bottlenecks.

FIGURE 4: (A) PERCENTILE PLOT (B)MORAN'S I SCATTER PLOT, (C) UNIVARIATE LOCAL INDICATORS OF SPATIAL ASSOCIATION (LISA) CLUSTER MAP AND, (D) LISA SIGNIFICANCE MAP FOR TOTAL HOSPITALS EMPANELLED PER ONE LAKH AYUSHMAN CARDS



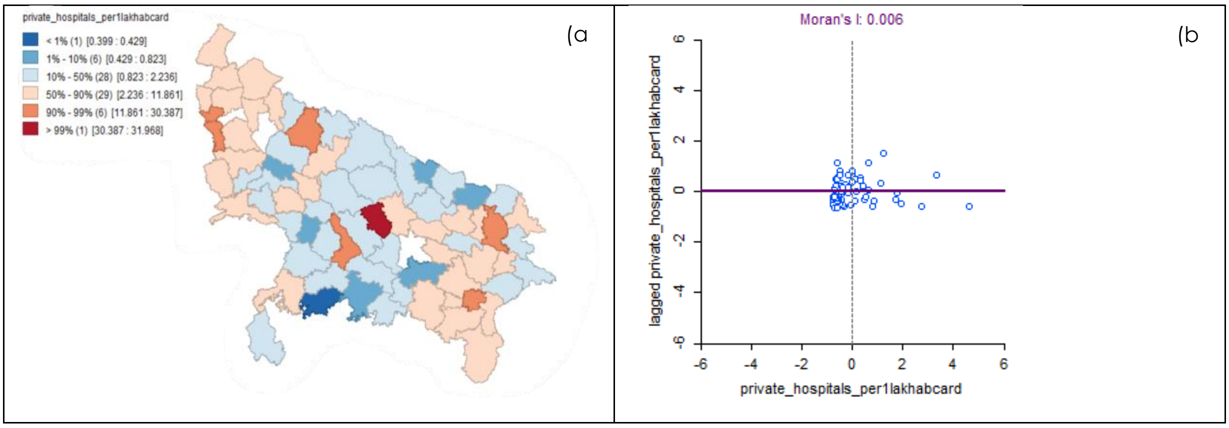
When examining the availability of public hospitals, districts like Jaunpur (9.93), Muzaffarnagar (9.76), Etawah (9.63) stand out in dark red for their higher public hospital densities. Moran's I value for public hospitals is 0.020(Figure 5), indicating very weak spatial autocorrelation, meaning that some clustering exists, but the spatial pattern is not strong or consistent.

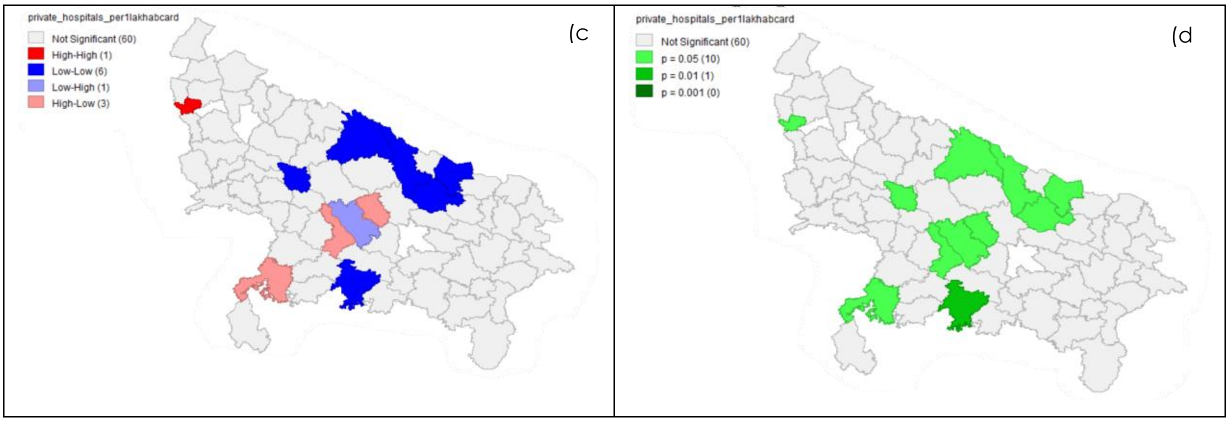
FIGURE 5: (A) PERCENTILE PLOT (B)MORAN'S I SCATTER PLOT, (C) UNIVARIATE LOCAL INDICATORS OF SPATIAL ASSOCIATION (LISA) CLUSTER MAP AND, (D) LISA SIGNIFICANCE MAP FOR PUBLIC HOSPITALS EMPANELLED PER ONE LAKH AYUSHMAN CARDS



In the case of private hospitals, urban districts dominate. Lucknow (31.96) has the highest private hospital density, followed by Kanpur Nagar (20.87), Gautam Buddha Nagar (24.43).On the other end, Mahoba (0.39), Kasganj (0.54), Shrawasti (0.62), and Siddharthnagar (0.57) show low private hospital densities, represented in dark blue. The LISA cluster map identifies Ghaziabad as a hotspot whereas Kheri, Bahraich, Banda, Balrampur, Gonda Farrukhabad are recognized as coldspots. Moran's I value for private hospitals is 0.006, indicating minimal spatial autocorrelation, suggesting that private hospital availability is highly localized and largely influenced by urbanization and market dynamics.

FIGURE 6: (A) PERCENTILE PLOT (B)MORAN'S I SCATTER PLOT, (C) UNIVARIATE LOCAL INDICATORS OF SPATIAL ASSOCIATION (LISA) CLUSTER MAP AND, (D) LISA SIGNIFICANCE MAP FOR PRIVATE HOSPITALS EMPANELLED PER ONE LAKH AYUSHMAN CARDS





FINDINGS FROM SPATIAL REGRESSION ANALYSIS

The figure 6 given below showcases the ordinary least squares and spatial regression results. The OLS model explained 74.63% of the variation in PMJAY utilization ($R^2 = 0.7463$). Ayushman card coverage exhibits a positive and highly significant association with admissions ($p < 0.001$), implying that districts with higher beneficiary identification records have greater utilization of PM-JAY hospital services. Similarly, the number of empanelled hospitals shows a statistically significant positive effect (β coeff. = 177.34, $p < 0.001$), underscoring the importance of provider availability in enabling scheme utilization. However, spatial diagnostics suggested the presence of spatial dependence. The Spatial Lag Model (SLM) produced a non-significant spatial autoregressive coefficient ($\rho = 0.0129$, $p = 0.9097$), indicating that utilization in one district does not directly influence utilization in neighbouring districts.

In contrast, the Spatial Error Model (SEM) yielded a statistically significant spatial error parameter ($\lambda = 0.3799$, $p = 0.0077$), confirming the presence of spatially correlated unobserved factors. The SEM also demonstrated superior model performance, with a higher R^2 (0.7668), lower AIC (1566.9), and improved log-likelihood (−774.44) relative to OLS and SLM. These findings suggest that spatial dependence operates through omitted regional characteristics rather than through direct inter-district spillover effects. Accordingly, the SEM was identified as the most appropriate specification for interpretation.

Ayushman Card Coverage was positively and highly significant ($\beta = 0.0490$, $p < 0.001$), indicating that districts with greater enrolment under PMJAY experience higher healthcare utilization. This highlights the critical role of beneficiary identification and scheme penetration in facilitating access. Similarly, the number of Empanelled Hospitals showed a strong positive association ($\beta = 192.95$, $p < 0.001$), underscoring the importance of healthcare infrastructure and provider availability in driving service uptake. Among structural determinants, Economic Vulnerability exhibited a significant negative association ($\beta = -33886.5$, $p = 0.0048$). Districts with higher proportions of economically disadvantaged populations demonstrated lower utilization levels, suggesting that financial risk protection alone may be insufficient to overcome entrenched structural barriers. PTR (Pupil–Teacher Ratio) Vulnerability was also negatively associated with utilization ($\beta = -20465.7$, $p = 0.027$), indicating that broader developmental deficits may indirectly constrain healthcare access.

In contrast, Female Vulnerability showed a positive and statistically significant relationship ($\beta = 41720.9$, $p = 0.0072$), potentially reflecting higher healthcare need or increased maternal and reproductive health service utilization in vulnerable districts. Overall, the spatial regression results demonstrate that both scheme-level factors, health infrastructure, and structural socioeconomic conditions significantly shape district-level variations in PMJAY healthcare utilization.

FIGURE 7: OLS, SLM AND SEM REGRESSION MODELS

Variable	OLS Coeff. (SE)	SLM Coeff. (SE)	SEM Coeff. (SE)
Intercept	-1895.29 (12336.1), *p* =0.8436	-2432.93 (12336.1), *p*= 0.8436	-10275 (13204.7), *p* =0.4364
Ayushman Cards	0.04668 (0.00912), *p* <0.001	0.04645 (0.0088), p<0.001	0.0490258 (0.00834), p<0.001
Empanelled Hospitals	177.34 (47.83), p<0.001	177.97 (44.83), p<0.001	192.946 (42.336), p<0.001
Economic Vulnerability	-41566.2 (11549.2), p<0.001	-41012.3 (11463.7), *p* <0.001	-33886.5 (12020.5), *p* =0.0048
Rural Pop. Vulnerability	8863.59 (15708.6), *p* =0.5746	8544.51 (14880.4), p=0.5658	8687.32 (14429), p=0.5471
Electricity Vulnerability	-7634.62 (20266.1), *p* =0.7076	-7038.25 (19358), *p* =0.7161	1151.09 (18582.2), *p* =0.9506
SC-ST Vulnerability	3190.64 (13463.1), *p* =0.8134	3063.03 (12591.1) , *p* =0.8078	238.269 (12698.1), *p* =0.9850
Female Vulnerability	47658.5 (14163.6), *p* =0.0013	47121.9 (13857.1) , p<0.001	41720.9 (15524.4), *p* =0.0072
PTR Vulnerability	-17984 (10233.4), p=0.0837	-18133.3 (9592.7), p=0.0587	-20465.7 (9263.87), p=0.02716
Spatial Lag ρ (SLM)	NA	0.0129276 (0.11407), p=0.9097	NA
Spatial Error λ (SEM)	NA	NA	0.37996 (0.14268), p=0.00775
R-squared	0.7463	0.74641	0.76684
AIC	1570.4	1572.39	1566.9
Log-Likelihood	-776.2	-776.196	-774.44

DISCUSSION

The spatial analysis reveals stark disparity in the implementation of PMJAY across districts of Uttar Pradesh, building on earlier observations of a mismatch between insurance coverage and healthcare access. Our spatial analysis confirms that private hospitals are disproportionately located in urban centres, reinforcing pre-existing service gaps in rural areas [23]. This was especially evident in clusters across Bundelkhand and Eastern UP, where both hospital density and service utilization remained low despite high vulnerability [2,4,5].The regression results highlight that Ayushman card distribution and the number of empanelled hospitals are key predictors of admissions. Districts such as Shrawasti, Bahraich, Kaushambi, and Sonbhadra exemplify this dynamic, with high vulnerability scores, weak infrastructure, and low utilization. This underpins the lens of Andersen's Behavioral Model of health services use as the amalgamation of predisposing, enabling and need factors at individual and community levels. These findings align with national patterns in aspirational districts, where private participation is limited, and public services are underutilized [12,13]. The spatial regression models confirm that healthcare access is not only structurally constrained but also geographically patterned. These findings underscore the need for tailored policy strategies that go beyond financial protection and address the spatial and structural roots of exclusion. Integrating spatial diagnostics into the PMJAY dashboard can support more equitable planning. This framework is scalable and replicable across other Indian states, and future research should incorporate longitudinal or patient-level data to assess temporal dynamics and causality [25]. In many underperforming districts, the presence of empanelled hospitals did not correlate strongly with service utilization—suggesting that structural barriers, such as literacy gaps limit effective demand. Conversely, districts with lower vulnerability and better private hospital access often converted card distribution into higher hospitalization rates.

The consistent negative association between PTR vulnerability and hospital admissions across all models suggests that educational disadvantage operates as a predisposing constraint. This finding aligns with the finding that alongside school education, health education is a significant determinant of health behavior[26]. The concentration of private hospitals in urban districts reflects market-driven supply responses, reinforcing Penchansky and Thomas' availability and accessibility dimensions. In high-vulnerability districts, the absence of private providers limits effective choice, resulting in underutilisation despite nominal insurance coverage. While this study identifies robust spatial associations, the findings should be interpreted as indicative of structural pathways rather than causal effects.

LIMITATIONS

The study used the data available on the PMJAY dashboard and the district wise development indicators. Data related to insurance claims, household hospital admissions, cultured vulnerability indicators can further supplement and confirm the findings of this study. A comprehensive volume of services are provided under the PMJAY via the public and private empanelled hospitals. However, the study could not include the package wise hospitilization, as the study was based on the indicators on the dashboard.

CONCLUSION

This study offers a spatially grounded evaluation of the PMJAY scheme's implementation across Uttar Pradesh, revealing key mismatches between health insurance coverage and actual healthcare access. Despite wide distribution of Ayushman cards and substantial hospital empanelment, many districts with high vulnerability remain underserved and underutilized. The spatial regression analysis identified Ayushman card distribution, hospital availability, and educational disadvantage (PTR) as consistent predictors of hospital admissions, while also highlighting the significance of spatial spillovers and unobserved local influences. The findings reinforce the importance of addressing geographic and structural barriers, such as low health literacy, uneven hospital distribution, and regional exclusion in policy design and implementation. For PMJAY to deliver on its promise of universal health coverage, policymakers must shift focus on the pre-existing, spatially entrenched inequalities in health infrastructure and social development.

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