

Spatial pattern and state-level variation in multimorbidity among older adults in India: a spatial and multilevel analysis of the Longitudinal Ageing Study in India (LASI)

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Abstract— Multimorbidity is rising among older Indians, and states differ in epidemiological transition. Whether it is spatially clustered, and whether state of residence matters beyond individual characteristics, remains untested. The study mapped and tested spatial autocorrelation of multimorbidity and nine chronic conditions across states/UTs and quantified state-level variation. Wave 1 (2017–18) of the Longitudinal Ageing Study in India provided 31,810 adults aged ≥ 60 from 36 states/UTs. Multimorbidity was ≥ 2 of nine self-reported, physician-diagnosed conditions. State prevalence was mapped; global and local Moran's I assessed clustering; a two-level random-intercept logistic model estimated adjusted odds ratios (AOR), intraclass correlation (ICC) and median odds ratio (MOR). Prevalence was 24.1% (range 6.5–51.8%). Multimorbidity was spatially clustered (Moran's I = 0.430, pseudo- $p < 0.001$), as were diabetes, bone/joint disease, hypertension and high cholesterol. A hot spot lay in the south and a cold spot in Assam. Urban residence (AOR 1.56), ADL limitation (1.63), IADL limitation (1.46), education (1.34) and working (1.40) raised the odds; caste category lowered them (0.72). State-level variance was 0.202 (ICC 5.8%; MOR 1.54). Multimorbidity is geographically structured and varies between states beyond individual composition. Self-reported diagnoses may understate burden in low-prevalence areas. State-differentiated care and surveillance are warranted.

Keywords: India, LASI, Moran's I, multilevel analysis, multimorbidity, older adults

I. INTRODUCTION

India's population is ageing rapidly: adults aged 60 years and above numbered about 149 million in 2022 and are projected to reach about 347 million by 2050 [1]. This demographic shift coincides with an epidemiological transition in which non-communicable diseases (NCDs) now account for a larger share of disease burden than communicable, maternal, neonatal and nutritional conditions, a crossover that occurred across Indian states about 24 years apart [2]. A defining feature of this transition in later life is multimorbidity, the co-occurrence of two or more chronic conditions in one person, which affects roughly one in three adults worldwide and a higher share of older adults [3,4]. Multimorbidity complicates clinical management, raises health-service use and household costs, and challenges health systems organised around single diseases [3,5].

What distinguishes India is the scale of its internal diversity. States and union territories differ markedly in epidemiological transition stage, age structure, urbanisation, socioeconomic development and health-system capacity [2]. State-level analyses show strong geographic heterogeneity in individual NCDs such as diabetes [6], and Kerala combines favourable health indicators with a high reported burden of hypertension, diabetes and related risk factors [7]. Studies based on the Longitudinal Ageing Study in India (LASI) have reported prevalence of multimorbidity among adults aged ≥ 60 years of roughly one-quarter to one-

third, with the highest state-level estimates in Kerala and other southern and western states [8–10], and have identified older age, urban residence, higher education and wealth, and functional limitation as correlates [9,11,12].

Most of this evidence, however, describes state differences in tables or choropleth maps without testing whether the geographic distribution is spatially structured, that is, whether high- and low-prevalence states cluster in contiguous regions more than chance would produce. Spatial statistics such as Moran's I and Local Indicators of Spatial Association (LISA) have been applied in India to individual conditions, notably diabetes using district-level LASI and NFHS data [13], and in a six-district sample in Odisha for multimorbidity [14]. For multimorbidity itself, geospatial work at national scale has focused on adult men aged 15–54 years in NFHS-5 [15]. A parallel methodological gap concerns inference: many LASI analyses use single-level regression, which treats respondents as independent and cannot separate individual-level from contextual (state-level) sources of variation [16].

Research gap and objectives

On the available evidence, no study has jointly (a) tested the spatial autocorrelation and identified spatial clusters of multimorbidity and each of its principal component conditions among a nationally representative sample of Indian adults aged ≥ 60 years, and (b) quantified, within the same data, how much state-level variation remains after individual characteristics are accounted for. Without this evidence, it is unclear whether state-differentiated NCD and geriatric-care policy should target isolated states or contiguous regions, and whether state differences are explained by population composition or reflect state-level context.

The study therefore used LASI Wave 1 to (i) describe the state-wise prevalence of multimorbidity and nine chronic conditions; (ii) test the global and local spatial autocorrelation of each, thereby identifying hot spots, cold spots and spatial outliers; (iii) examine individual-level correlates; and (iv) estimate state-level variance, intraclass correlation and median odds ratio in a two-level random-intercept logistic model.

II. METHODS

This is a cross-sectional secondary analysis of nationally representative survey data. The study is reported following the STROBE guideline for cross-sectional studies [17].

Data source and sampling design

The study used Wave 1 (2017–18) of LASI, conducted by the International Institute for Population Sciences (IIPS) with the Harvard T.H. Chan School of Public Health and the University of Southern California [18,19]. LASI is representative of adults aged ≥ 45 years and their spouses at national and state/UT level; it interviewed 72,250 individuals using a multistage stratified area-probability cluster design, with three stages in rural and four stages in urban areas [18]. Individual sampling weights adjust for selection probabilities and non-response [19]. The analytic sample comprised 31,810 respondents aged ≥ 60 years with complete information on all nine chronic-condition indicators, distributed across 36 states and UTs (318 respondents in Arunachal Pradesh to 2,167 in Uttar Pradesh; Table 1). State and UT boundaries are those in force during fieldwork, so Daman and Diu and Dadra and Nagar Haveli are analysed separately and Ladakh is included within Jammu and Kashmir.

Outcome: multimorbidity

Multimorbidity is commonly defined as the coexistence of two or more chronic conditions, although the condition list and threshold vary across studies [20,21]. The study counted nine self-reported conditions that respondents reported had been diagnosed by a physician: hypertension, diabetes mellitus, cancer or malignant tumour, chronic lung disease, heart disease, stroke, bone or joint disease, neurological or psychiatric disease, and high cholesterol. Multimorbidity was coded 1 for ≥ 2 conditions and 0 otherwise. Because the outcome is based on diagnosed conditions, it measures diagnosed rather than total underlying disease burden [22].

Covariates

Individual-level covariates were age group (60–69, 70–79, ≥80 years), sex, caste (Scheduled Tribe/Scheduled Caste, Other Backward Class, other), religion (Hindu, Muslim, other), education (none, up to primary, secondary, graduate and above), working status (currently working, not working, never worked), residence (rural, urban), region (North, Central, East, Northeast, West, South), marital status, tobacco use, alcohol consumption, life satisfaction (low, medium, high) and household wealth (poorer/poorest/middle versus richer/richest, based on monthly per capita consumption expenditure quintiles [19]). Limitations in activities of daily living (ADL) and instrumental activities of daily living (IADL) were coded as any difficulty versus none, following the Katz and Lawton–Brody frameworks [23,24].

Descriptive and bivariate analysis

Weighted prevalence of multimorbidity and of each condition was estimated for every state/UT. Associations between covariates and multimorbidity were tested using weighted Pearson chi-square tests (Table 4).

Spatial analysis

Spatial analysis rests on the premise that nearby places tend to be more alike than distant ones [25]. The unit of analysis was the state/UT. The study defined neighbours by first-order queen contiguity (shared border or vertex) and row-standardised the weights matrix. Lakshadweep and the Andaman and Nicobar Islands have no land neighbours and were excluded from the spatial weights, leaving 34 units; their prevalence is shown in Table 1 and Fig. 1. Global spatial autocorrelation was measured with Moran's I [26] for multimorbidity and each condition, with inference by 9,999 random permutations (pseudo-*p* values). Positive values indicate that similar prevalence cluster in space, negative values indicate dispersion, and the expected value under spatial randomness is $-1/(n - 1) = -0.030$. Local clusters were identified with univariate Local Moran's I (LISA) [27] using conditional permutation (4,999 permutations), classifying units as high–high (hot spots), low–low (cold spots) or high–low/low–high (spatial outliers). Because there are only 34 units and many local tests, local results are exploratory; the study reported $p < 0.05$ as significant and $0.05 \leq p < 0.10$ as suggestive, without multiplicity adjustment. Methods and terminology follow those implemented in GeoDa [28]. Choropleth maps used five classes for each indicator.

Multilevel analysis

Respondents sharing a state may resemble each other for unmeasured contextual reasons, violating the independence assumption of single-level regression [16,29]. The study therefore fitted a two-level random-intercept logistic model with individuals (level 1) nested in states/UTs (level 2), as given in equation 1:

$$\text{logit}(\pi_{ij}) = \beta_0 + x_{ij}^T \beta + u_j, \quad u_j \sim N(0, \sigma_u^2) \quad (1)$$

where π_{ij} is the probability of multimorbidity for individual *i* in state *j*, x_{ij} the covariates, β the fixed-effect coefficients and u_j the state-level random intercept. The model included all covariates listed above simultaneously; ordered covariates entered as single terms, so each AOR is the change in odds per one-category step as coded in Table 5. Random effects were summarised as the state-level variance σ_u^2 with its 95% confidence interval, the latent-variable intraclass correlation (ICC; equation 2) [29,30], and the median odds ratio (MOR; equation 3), which expresses state-level heterogeneity on the odds-ratio scale and is directly comparable with fixed-effect odds ratios [31,32].

$$\text{ICC} = \sigma_u^2 / (\sigma_u^2 + \pi^2 / 3) \quad (2)$$

$$\text{MOR} = \exp[\sqrt{(2\sigma_u^2)} \times 0.6745] \quad (3)$$

Clustering was tested by a likelihood-ratio test against an otherwise identical single-level logistic model; because the null value of the variance lies on the boundary of the parameter space, the reference distribution is a 50:50 mixture of χ^2 distributions [33]. With 36 groups, the variance estimate is imprecise and should be read with its confidence interval [34]. Survey weights were applied to account for the complex sampling design [35]. Statistical significance was set at $p < 0.05$. Analyses were performed

in Stata 17.0 (StataCorp, College Station, TX, USA); spatial statistics were computed with permutation tests in Python and can be replicated in GeoDa.

Ethics

This study analysed de-identified, publicly available secondary data. LASI obtained ethical clearance and written informed consent during original data collection [18]; no additional approval was required.

III. RESULTS

Sample and state-wise prevalence

Table 1 shows the state-wise sample, weighted share and prevalence of multimorbidity and each condition. The largest weighted shares came from Uttar Pradesh (12.5%), Maharashtra (12.0%), Bihar (9.0%) and West Bengal (8.2%). National multimorbidity prevalence was 24.1%. State/UT prevalence ranged from 6.5% in Nagaland to 51.8% in Kerala, an almost eight-fold difference (median 23.9%, interquartile range 16.5–33.3%). The ten highest prevalences were in Kerala (51.8%), Chandigarh (40.8%), Lakshadweep (38.1%), Goa (37.9%), Jammu and Kashmir (35.6%), Puducherry (35.5%), the Andaman and Nicobar Islands (35.2%), West Bengal (34.7%), Punjab (33.7%) and Karnataka (33.2%); Andhra Pradesh (33.1%) and Telangana (29.1%) followed closely. The lowest were in Nagaland (6.5%), Meghalaya (9.8%), Chhattisgarh (11.1%), Jharkhand (12.2%), Arunachal Pradesh (13.1%), Uttar Pradesh (13.5%) and Madhya Pradesh (14.0%). Kerala's level was driven by hypertension (51.6%), diabetes (35.8%) and high cholesterol (25.3%), whereas West Bengal's was driven mainly by bone/joint disease (32.9%), with the country's highest stroke (6.2%) and neuro-psychiatric (8.9%) prevalence among the larger states. Estimates for very small UTs (e.g. Chandigarh, Lakshadweep, Daman and Diu) rest on populations that contribute under 0.1% of the weighted sample and should be read cautiously. Fig. 1 maps the distribution of each condition and of multimorbidity.

Table 1. State/UT-wise sample size, weighted share, and weighted prevalence (%) of multimorbidity and nine chronic conditions among adults aged ≥ 60 years, LASI Wave 1 (2017–18)

State / UT	n	Wtd %	Multi-morbidity	Hypertension	Diabetes	Cancer	Chronic lung	Heart disease	Stroke	Bone/ joint	Neuro/ psych	High chol.
Jammu and Kashmir	730	1.11	35.6	48.5	9.9	0.30	7.6	10.4	3.8	27.4	5.4	3.8
Himachal Pradesh	618	0.64	24.2	38.1	15.9	2.84	5.1	9.0	3.1	14.4	0.8	4.8
Punjab	1,003	2.09	33.7	49.5	19.0	0.63	6.4	5.8	3.1	16.6	2.7	13.4
Chandigarh	389	0.04	40.8	50.4	24.5	0.84	4.6	16.5	4.1	13.5	4.5	10.6
Uttarakhand	641	0.76	16.2	27.4	9.9	1.38	7.9	3.9	1.2	15.6	1.0	0.6
Haryana	847	2.11	18.7	41.0	9.4	1.00	10.1	4.1	1.0	10.3	1.0	2.2
Delhi	495	0.94	31.1	45.6	26.8	0.69	9.3	9.3	4.3	14.0	1.8	1.6
Rajasthan	1,076	4.94	20.3	31.3	9.1	0.59	15.1	2.7	1.5	15.2	1.5	1.0
Uttar Pradesh	2,167	12.45	13.5	21.3	8.4	0.37	7.8	2.3	2.6	11.1	2.3	0.7
Bihar	1,806	9.03	17.9	27.9	8.4	0.30	7.1	7.4	1.7	13.5	0.6	1.6
Sikkim	437	0.03	23.6	54.2	17.1	0.00	1.6	5.4	0.4	11.3	1.5	0.8
Arunachal Pradesh	318	0.11	13.1	26.6	8.5	0.56	4.4	0.3	2.0	13.2	1.2	0.0



State / UT	n	Wtd %	Multi-morbidity	Hyper-tension	Diabetes	Cancer	Chronic lung	Heart disease	Stroke	Bone/ joint	Neuro/ psych	High chol.
Nagaland	603	0.12	6.5	15.1	6.8	0.08	1.0	0.4	1.4	3.6	5.3	0.4
Manipur	605	0.27	18.3	33.2	11.7	1.10	3.7	4.0	3.6	6.1	1.6	5.3
Mizoram	531	0.09	16.5	31.3	9.2	1.17	8.9	1.2	3.3	9.1	3.3	0.8
Tripura	460	0.30	20.3	36.9	11.0	0.70	9.3	3.8	3.9	10.7	2.5	0.9
Meghalaya	411	0.17	9.8	35.4	5.5	0.19	1.9	1.4	0.8	4.4	1.4	1.1
Assam	811	1.91	16.5	40.2	8.7	0.40	4.7	4.2	2.7	6.4	2.2	0.5
West Bengal	1,540	8.24	34.7	36.8	11.5	1.13	11.4	7.4	6.2	32.9	8.9	1.5
Jharkhand	1,168	2.53	12.2	25.4	11.7	0.68	3.8	2.5	1.1	7.8	0.6	0.3
Odisha	1,235	3.95	17.0	26.9	9.8	0.45	4.8	1.3	2.3	17.6	1.3	1.4
Chhattisgarh	779	1.61	11.1	20.1	9.2	0.48	3.5	1.1	1.8	9.1	1.0	0.2
Madhya Pradesh	1,313	7.00	14.0	21.9	7.8	0.19	8.6	2.8	1.2	10.1	1.9	2.2
Gujarat	984	5.05	26.6	31.7	18.1	1.63	8.6	5.3	2.6	21.6	2.8	4.0
Daman and Diu	429	0.01	32.3	38.9	19.2	0.60	4.1	3.4	2.0	31.2	0.9	7.1
Dadra and Nagar Haveli	450	0.02	19.3	20.6	10.1	0.23	9.8	1.0	0.6	23.6	3.4	2.6
Maharashtra	1,786	12.00	28.3	37.2	16.4	0.85	7.3	6.8	4.2	26.6	1.3	1.5
Andhra Pradesh	1,098	3.92	33.1	43.8	19.9	0.33	10.2	4.6	3.0	24.0	3.7	1.0
Karnataka	1,001	6.66	33.2	40.3	26.8	1.62	12.0	9.2	2.2	28.9	2.2	4.4
Goa	633	0.11	37.9	57.7	26.8	0.86	4.0	7.0	6.7	15.3	3.2	8.6
Lakshadweep	500	<0.01	38.1	45.0	28.3	0.56	7.3	5.8	5.3	16.9	0.4	17.5
Kerala	1,206	2.01	51.8	51.6	35.8	2.03	12.8	13.6	2.6	27.6	2.2	25.3
Tamil Nadu	1,530	7.11	29.2	33.2	23.5	0.07	7.5	4.2	1.8	26.3	5.2	2.6
Puducherry	638	0.11	35.5	41.8	27.3	0.41	13.9	7.5	0.7	22.8	6.9	6.8
Andaman and Nicobar	521	0.02	35.2	47.0	17.9	0.81	5.8	6.0	3.4	23.6	4.0	2.8
Telangana	1,051	2.50	29.1	40.3	13.9	0.59	5.7	3.3	2.5	33.5	8.1	0.3
India	31,810	100.00	24.1	32.8	14.3	0.71	8.5	5.2	2.7	19.7	2.8	2.5

n, unweighted number of respondents. Wtd %, state share of the weighted analytic sample. Prevalence estimates are weighted percentages. Chol., cholesterol.

Spatial autocorrelation and clusters

Multimorbidity showed significant positive global spatial autocorrelation (Moran's $I = 0.430$, $z = 3.69$, pseudo- $p < 0.001$; Table 2): 27 of the 34 states/UTs (79%) lay in the high-high or low-low quadrants of the Moran scatterplot (Fig. 2). Positive and significant autocorrelation was also found for diabetes ($I = 0.502$), bone/joint disease ($I = 0.442$), hypertension ($I = 0.290$), high cholesterol ($I = 0.212$) and, marginally, heart disease ($I = 0.185$, $p = 0.047$) and chronic lung disease ($I = 0.171$, $p = 0.056$). Cancer, stroke and neuro-psychiatric conditions showed no evidence of spatial clustering (I between -0.159 and -0.075 ; all $p > 0.6$ for a positive association). After a Bonferroni correction for the ten global tests ($\alpha = 0.005$), multimorbidity, diabetes and bone/joint disease remained significant (figure 1).

Table 2. Global spatial autocorrelation (Moran's I) of state/UT-level prevalence of multimorbidity and chronic conditions, adults aged ≥ 60 years, LASI Wave 1

Indicator	Moran's I	z-score	Pseudo-p	Pattern
Multimorbidity	0.430	3.69	<0.001	Clustered
Hypertension	0.290	2.55	0.008	Clustered
Diabetes	0.502	4.31	<0.001	Clustered
Cancer	-0.075	-0.38	0.626	Random
Chronic lung disease	0.171	1.62	0.056	Weak / borderline
Heart disease	0.185	1.80	0.047	Weak / borderline
Stroke	-0.159	-1.06	0.857	Random
Bone/joint disease	0.442	3.82	<0.001	Clustered
Neuro-psychiatric conditions	-0.152	-1.01	0.851	Random
High cholesterol	0.212	2.35	0.024	Clustered

$n = 34$ states/UTs (Lakshadweep and Andaman and Nicobar Islands excluded: no contiguous neighbours). Queen contiguity, row-standardised weights; 9,999 permutations; expected $I = -0.030$. Pseudo-p is one-sided for positive autocorrelation.

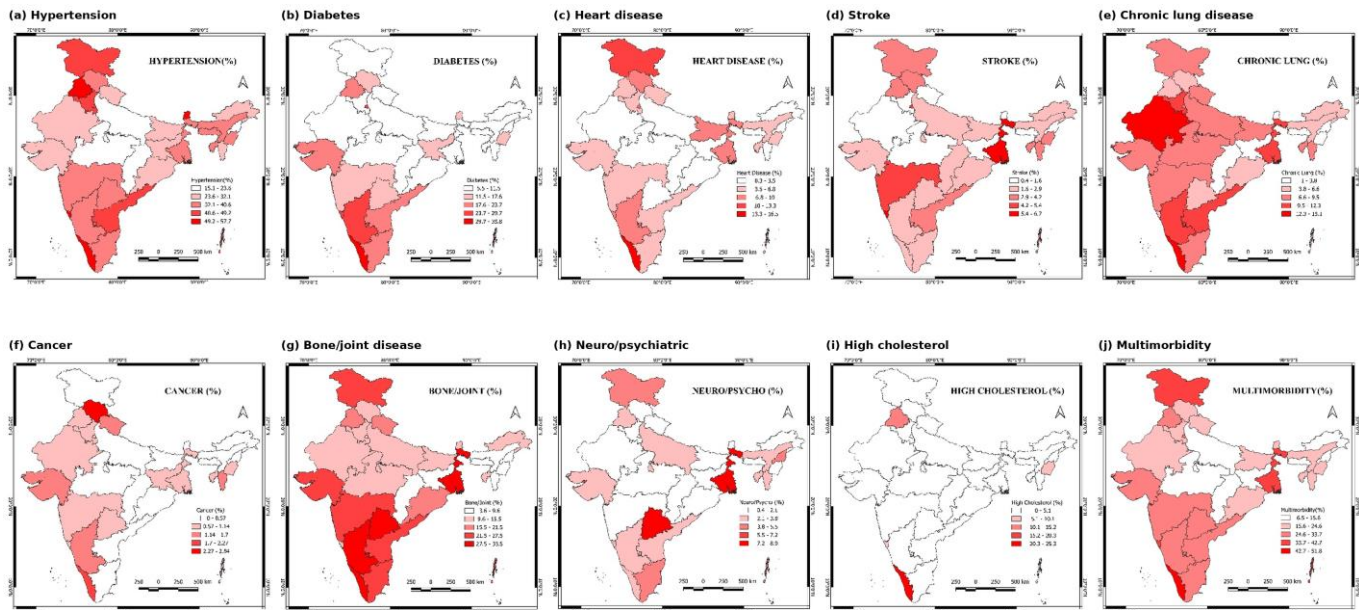


Figure 1. State/UT-wise spatial variation in the prevalence of chronic conditions and multimorbidity among adults aged ≥ 60 years in India, LASI Wave 1 (2017–18). Panels show (a) hypertension, (b) diabetes, (c) heart disease, (d) stroke, (e) chronic lung disease, (f) cancer, (g) bone/joint disease, (h) neuro-psychiatric conditions, (i) high cholesterol and (j) multimorbidity.

Darker shades denote higher prevalence; class intervals differ between panels and are given in each legend.

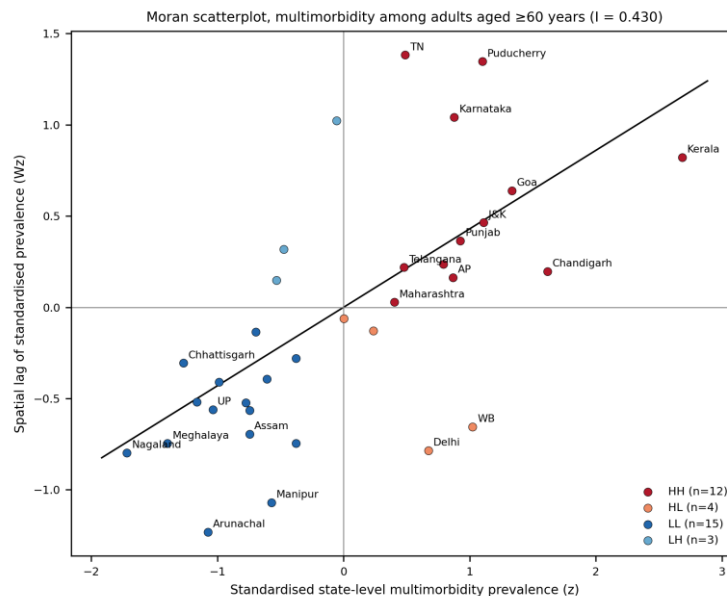


Figure 2. Moran scatterplot of state/UT-level multimorbidity prevalence among adults aged ≥ 60 years. The slope of the fitted line equals Moran's I (0.430). HH, high–high; LL, low–low; HL, high–low; LH, low–high.

Local analysis (Table 3) identified a hot spot of multimorbidity in the peninsular south Karnataka ($p = 0.004$), Tamil Nadu ($p = 0.003$) and Puducherry ($p = 0.012$) and a cold spot in Assam ($p = 0.044$), with suggestive low–low clustering in Uttar Pradesh, Arunachal Pradesh and Manipur ($p = 0.053$ – 0.057). The southern hot spot was also evident for diabetes (Kerala, Tamil Nadu, Karnataka, Puducherry) and bone/joint disease (Karnataka, Tamil Nadu, Kerala, Puducherry; Andhra Pradesh suggestive), whereas low–low clusters for bone/joint disease lay in the north-east (Manipur, Arunachal Pradesh, Mizoram). No spatial outlier

was significant for multimorbidity, although four states lay in the high–low quadrant (West Bengal, Delhi, Gujarat, Himachal Pradesh), reflecting high prevalence next to lower-prevalence neighbours; West Bengal was a suggestive high–low outlier for bone/joint disease ($p = 0.099$).

Table 3. Local spatial clusters (Local Moran's I) of multimorbidity and selected conditions among adults aged ≥ 60 years, LASI Wave 1

Indicator	Hot spots (high–high), $p < 0.05$	Cold spots (low–low), $p < 0.05$	Suggestive, $0.05 \leq p < 0.10$
Multimorbidity	Karnataka (0.004), Tamil Nadu (0.003), Puducherry (0.012)	Assam (0.044)	Uttar Pradesh (0.056), Arunachal Pradesh (0.057), Manipur (0.053)
Diabetes	Kerala (0.002), Tamil Nadu (<0.001), Karnataka (0.004), Puducherry (0.007)	Assam (0.020)	Jharkhand (0.082), Manipur (0.088)
Bone/joint disease	Karnataka (0.004), Tamil Nadu (0.017), Kerala (0.044), Puducherry (0.048)	Manipur (0.021), Arunachal Pradesh (0.040), Mizoram (0.048)	HH: Andhra Pradesh (0.054); LL: Assam (0.053), Uttar Pradesh (0.060), Nagaland (0.067); LH: Sikkim (0.055), Goa (0.063); HL: West Bengal (0.099)
Hypertension	Karnataka (0.041)	Jharkhand (0.030)	Madhya Pradesh, LL (0.076); Tamil Nadu, LH (0.095)

Pseudo-p values in parentheses (4,999 conditional permutations; queen contiguity; $n = 34$). HH, high–high; LL, low–low; LH, low–high; HL, high–low. Local results are exploratory because of the small number of units.

Individual-level correlates

Table 4 presents bivariate associations. Multimorbidity prevalence was higher among urban than rural residents (36.0% vs 19.1%), among those with secondary education or above than with no formal education (35.6% vs 18.4%), and among those not working or who never worked than among the currently working (27.3% and 31.0% vs 13.2%). It was higher among those with ADL limitation (33.1% vs 21.2%) or IADL limitation (28.7% vs 19.7%) and in the richer/richest wealth group (31.6% vs 19.8%). By region, prevalence was highest in the South (33.1%) and West (27.8%) and lowest in the Central (13.5%) and Northeast (16.1%) regions. Prevalence also increased from Scheduled Tribe/Scheduled Caste (17.0%) through Other Backward Class (25.2%) to other castes (29.1%), and was lower among tobacco users (19.6% vs 26.9%) and alcohol users (19.9% vs 24.7%) than non-users. All associations were significant ($p < 0.001$ except marital status, $p = 0.019$).

Table 4. Bivariate association between covariates and multimorbidity among adults aged ≥ 60 years, LASI Wave 1

Covariate	n (unweighted)	Multimorbidity (%)	p-value
Age group			<0.001
60–69 years	19,162	22.84	
70–79 years	9,221	26.22	
≥ 80 years	3,427	24.61	
Sex			<0.001



Covariate	n (unweighted)	Multimorbidity (%)	p-value
Male	15,277	22.45	<0.001
Female	16,533	25.48	
Caste			
ST/SC	10,463	17.04	
OBC	12,101	25.18	
Others	9,246	29.05	
Religion			<0.001
Hindu	23,230	23.25	
Muslim	3,720	26.97	
Others	4,860	29.28	
Education			<0.001
No formal education	17,155	18.44	
Up to primary	7,626	28.24	
Secondary	5,718	35.59	
Graduate and above	1,311	31.79	<0.001
Working status			
Currently working	9,036	13.22	
Currently not working	13,738	27.28	
Never worked	9,036	30.98	<0.001
Residence			
Rural	21,041	19.14	
Urban	10,769	36.00	



Covariate	n (unweighted)	Multimorbidity (%)	p-value
Region			<0.001
North	5,799	24.39	
Central	4,259	13.49	
East	5,749	22.94	
Northeast	3,739	16.12	
West	4,282	27.84	
South	7,982	33.12	
Marital status			0.019
Currently married	20,154	23.31	
Never married	310	15.94	
Widowed	10,816	25.62	
Others	530	20.30	
ADL limitation			<0.001
No	24,971	21.24	
Yes	6,785	33.05	
IADL limitation			<0.001
No	17,701	19.72	
Yes	14,023	28.68	
Tobacco use			<0.001
No	19,377	26.94	
Yes	12,242	19.61	
Alcohol consumption			<0.001

Covariate	n (unweighted)	Multimorbidity (%)	p-value
No	26,201	24.72	
Yes	5,424	19.85	
Life satisfaction			<0.001
Low	9,401	23.05	
Medium	7,394	22.21	
High	14,001	25.18	
Wealth group			<0.001
Poorer/poorest/middle	19,592	19.82	
Richer/richest	12,218	31.63	
Total sample	31,810	24.05	

Multimorbidity percentages are weighted row percentages; p-values from Pearson chi-square tests. ST/SC, Scheduled Tribe/Scheduled Caste; OBC, Other Backwards Class; ADL, activities of daily living; IADL, instrumental activities of daily living.

Multilevel analysis

In the two-level model (Table 5; 30,740 observations in 36 states/UTs), urban residence (AOR 1.56, 95% CI 1.46–1.67), ADL limitation (AOR 1.63, 1.52–1.75) and IADL limitation (AOR 1.46, 1.36–1.55) were the strongest correlates, followed by working status (AOR 1.40), education (1.34), religion (1.13) and region (1.10). Caste category was associated with lower odds (AOR 0.72, 0.67–0.78). Age, sex, marital status, tobacco use, alcohol consumption and life satisfaction were not significantly associated with multimorbidity after adjustment. The state-level variance was 0.202 (95% CI 0.122–0.335), corresponding to an ICC of 5.8% (95% CI 3.6–9.2%) and a MOR of 1.54 (95% CI 1.40–1.74): for two otherwise similar older adults living in two randomly chosen states, the one in the higher-risk state had a median 54% higher odds of multimorbidity. The likelihood-ratio test against a single-level model was highly significant ($\chi^2 = 605.55$, $p < 0.001$), indicating substantial clustering by state.

Table 5. Two-level random-intercept logistic regression of multimorbidity among adults aged ≥ 60 years, LASI Wave 1

Variable	AOR / estimate	95% CI	p-value
Age category	0.993	0.950–1.038	0.755
Sex	0.990	0.916–1.071	0.806
Caste	0.721	0.671–0.775	<0.001
Religion	1.133	1.082–1.187	<0.001

Variable	AOR / estimate	95% CI	p-value
Working status	1.401	1.337–1.467	<0.001
Education	1.344	1.296–1.393	<0.001
Place of residence	1.561	1.463–1.665	<0.001
Region	1.098	1.013–1.189	0.023
Marital status	0.971	0.940–1.002	0.069
ADL limitation	1.630	1.517–1.750	<0.001
IADL limitation	1.455	1.364–1.553	<0.001
Tobacco use	0.945	0.883–1.012	0.108
Alcohol consumption	1.012	0.927–1.106	0.786
Life satisfaction	1.016	0.982–1.051	0.374
Random effects and diagnostics			
State-level variance, σ^2_u	0.202	0.122–0.335	—
ICC (latent scale), %	5.8	3.6–9.2	—
Median odds ratio (MOR)	1.54	1.40–1.74	—
LR test vs single-level logistic model	$\chi^2 = 605.55$		<0.001
Observations / states	30,740 / 36		
Wald $\chi^2(14)$; log likelihood	1,584.59; –15,451.21		<0.001

AOR, adjusted odds ratio; CI, confidence interval; ICC, intraclass correlation coefficient. Ordered covariates were entered as single terms (AOR per one-category step as coded). ICC and MOR were computed from the reported variance and its confidence limits: $ICC = \sigma^2_u / (\sigma^2_u + \pi^2/3)$; $MOR = \exp(0.6745 \times \sqrt{(2\sigma^2_u)})$.

IV. DISCUSSION

In this nationally representative analysis of older Indians, multimorbidity was not randomly distributed across states. Prevalence varied almost eight-fold between states, high- and low-prevalence states formed contiguous clusters (Moran's $I = 0.43$), and a statistically significant state-level variance persisted after adjustment for individual characteristics (MOR 1.54). Three findings merit critical interpretation: the geography of the clusters, the extent to which they reflect detection rather than disease, and the relationship between spatial and multilevel evidence.

The hot spot in Karnataka, Tamil Nadu and Puducherry, with Kerala and the west-coast states also high, and the cold belt across central and north-eastern India broadly mirror the gradient of epidemiological transition in which southern states reached NCD dominance earlier than central and north-eastern states [2]. The southern concentration of diabetes observed in the study is in line with district-level analyses of LASI and NFHS data [13] and with state-level diabetes estimates [6]. That multimorbidity

clusters more strongly than hypertension or heart disease, and that it follows diabetes and bone/joint disease most closely, suggests the spatial signal is carried chiefly by a few highly prevalent conditions rather than by all conditions equally. The absence of clustering for cancer, stroke and neuro-psychiatric conditions should not be taken as proof of spatial randomness: their prevalence is low, state estimates are imprecise, and a test on 34 units has limited power. The cold spot is also statistically fragile: only Assam met the 5% threshold, and Uttar Pradesh, Arunachal Pradesh and Manipur were borderline, so the north-eastern and central cold zones should be treated as a hypothesis for district-level confirmation. The prominent high-low profile of West Bengal, driven by bone/joint disease, stroke and neuro-psychiatric prevalence that exceed those of its neighbours, is likewise unlikely to reflect a single cause; differences in reporting of arthritis and neurological symptoms, interviewer or language effects, and true differences in burden cannot be separated with these data.

The outcome counts conditions that a physician has diagnosed. In India, diagnosed chronic conditions are more common among socially and economically advantaged groups, whereas disadvantaged groups are more likely to remain untreated even when diagnosed [22]. Measured blood pressure and glucose surveys also find that large fractions of hypertension and diabetes are undiagnosed and that undiagnosed disease varies sharply across districts [36]. The observed pattern, with the highest prevalence in the best-resourced, most urban and most educated states and among urban residents and the richest quintile, is therefore what one would expect if detection, as well as disease, varies spatially. This is consistent with the Kerala paradox, in which strong health indicators coexist with high reported NCD burden [7]. Two implications follow. First, the cold spots should not be read as areas of good health; they may be areas of limited diagnostic reach. Second, hot spots are not necessarily where unmet need is greatest. The cross-sectional data cannot adjudicate between these explanations, and the claim should be tested with biomarker-confirmed multimorbidity from LASI [18]. The same caution applies to the lower odds of multimorbidity in the Scheduled Tribe/Scheduled Caste and tobacco-using groups: these differences may partly reflect under-diagnosis, survivor effects or measurement, and the study did not test these mechanisms.

The two analyses answer different questions. Moran's I describes the spatial arrangement of observed state prevalences, which combine population composition and context; the random-intercept model asks how much between-state variation remains after composition is held constant. An ICC of 5.8% may seem small, but on the odds-ratio scale a MOR of 1.54 is comparable in size with the effects of urban residence (AOR 1.56) and ADL limitation (AOR 1.63) and larger than that of education or religion, so state of residence matters about as much as the strongest individual predictors. Two features of the model temper this interpretation. First, region was included as a fixed effect and therefore absorbs part of the broad south-west versus central-north-east gradient that the Moran statistic detects; the remaining variance describes differences among states within regions, which the global statistic may under- or over-state. Second, covariates such as education, residence and wealth probably lie on the pathway between state context and diagnosed disease, so adjusting for them may understate the contextual effect, while omitted state-level factors (health-system density, screening programmes, population age structure, diet, obesity) may inflate or attenuate it. With only 36 clusters the variance confidence interval is wide (0.122–0.335), and the state intercept is a proxy for a bundle of contextual influences rather than evidence of any single causal mechanism [16,34].

The national estimate of the study (24.1%) is lower than the 32.1% reported for the same wave using eleven conditions among 31,464 older adults, and the Kerala estimate (51.8%) is lower than the 59.2% in that study [8]. Differences in the condition list, the threshold and the complete-case restriction explain level differences, which underlines that multimorbidity prevalence depends strongly on its operational definition [20,21]; the relative ranking of states, with Kerala highest and the central and north-eastern states lowest, is consistent across studies [8,9]. The associations with urban residence, education, working status and functional limitation agree with earlier national analyses [9,11,12]. The spatial results complement the only prior geographic multimorbidity analyses identified: a six-district convenience sample in Odisha, in which a negative Moran's I reflected the small and purposively selected set of districts rather than a national pattern [14], and a study of men aged 15–54 years in NFHS-5 [15]; neither addresses older adults nationally.

Strengths include a large, nationally representative sample covering all states and UTs, combined spatial and multilevel inference on the same outcome, reporting of ICC and MOR rather than variance alone, and analysis of each component condition. Limitations should be weighed. (1) The outcome is self-reported physician diagnosis, so under-diagnosis, recall bias and differential access shape state estimates. (2) The unit of spatial analysis is the state, which is large and heterogeneous; state-level clustering may mask district-level patterns and is subject to the modifiable areal unit problem and ecological inference limits, and the study could not use district identifiers. (3) Moran's I was computed on point estimates without accounting for sampling error, which is large for small states and UTs; two island UTs had to be excluded from the weights, and local results are exploratory with no multiplicity correction. (4) The multilevel model assumes constant covariate effects across states, treats ordered covariates as single terms, and rests on 36 clusters. (5) The cross-sectional design precludes causal or temporal inference, including for the association between functional limitation and multimorbidity, which is probably bidirectional. (6) The nine-condition list omits conditions such as depression, chronic kidney disease and osteoporosis, and the findings apply to adults aged ≥ 60 years in 2017–18 and may have changed.

V. POLICY IMPLICATIONS AND RECOMMENDATIONS

The following recommendations follow from the findings but rest on cross-sectional, ecological and self-reported data; they identify priorities for planning and further study rather than proven interventions.

Differentiate NCD and geriatric strategies by regional multimorbidity profile

Because high-burden states cluster in the peninsular south and west, state programmes there should move beyond single-disease vertical delivery towards integrated, person-centred management of multimorbidity within primary care: multi-condition clinical protocols, structured medication review to limit polypharmacy, and linkage between NCD clinics and geriatric and long-term-care services. These are natural extensions of the existing NP-NCD and the National Programme for Health Care of Elderly [37,38].

Prioritise case-finding in low-prevalence belts before concluding that burden is low

In the central and north-eastern cold zones, population-based screening for hypertension and diabetes among people aged ≥ 60 years, backed by diagnostic and drug availability at the first level of care, should precede any reallocation of resources, because low recorded prevalence may signal under-diagnosis [22,36]. The strong association of ADL and IADL limitation with multimorbidity supports using routine functional assessment as a low-cost trigger for NCD testing in these settings.

Plan across state borders where clusters cross them

The southern hot spot spans several adjacent states, and the cold zone spans several north-eastern states. Inter-state mechanisms for sharing referral networks, clinical guidance, workforce training and surveillance would suit clusters better than separate state plans.

Investigate state-specific outliers before acting

West Bengal's unusually high bone/joint, stroke and neuro-psychiatric prevalence warrants validation (data quality and reporting) followed by targeted musculoskeletal, rehabilitation and stroke services if confirmed. Similar verification is warranted for small UTs with extreme values.

Protect households from the cost of chronic care

As detection improves, more older people will need long-term treatment. Extending financial protection and free essential-drug provision for outpatient chronic care for older people, building on schemes such as PM-JAY [39], would reduce the risk that better diagnosis shifts burden from health to household finances.

Reach groups that are diagnosed least and treated least

Mobile screening, community health worker visits and outreach for rural residents, people with no formal education and disadvantaged caste groups should accompany infrastructure investment, since these groups are more likely to remain undiagnosed or untreated [22].

Build spatially disaggregated surveillance

State health dashboards should report multimorbidity and component-condition prevalence with confidence intervals, together with spatial indicators and multilevel summaries such as the MOR, and should use biomarker-confirmed measures where available so that changes in detection can be separated from changes in disease. Future LASI waves and district-level estimation would allow the hot- and cold-spot hypotheses reported here to be tested at the scale at which services are organised.

VI. CONCLUSION

Multimorbidity among older adults in India is geographically structured: states with high prevalence cluster in the peninsular south and west, states with low prevalence cluster across central and north-eastern India, and state of residence remains associated with multimorbidity after individual characteristics are taken into account (ICC 5.8%, MOR 1.54). Because the measure reflects diagnosed disease, the low-prevalence belts may combine lower burden with under-diagnosis. Policy should therefore pair integrated multimorbidity care in high-burden clusters with active case-finding elsewhere, coordinate across contiguous states, and invest in spatially disaggregated, biomarker-supported surveillance.

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REFERENCES

1. International Institute for Population Sciences and United Nations Population Fund, “India Ageing Report 2023: Caring for Our Elders – Institutional Responses”, UNFPA India, New Delhi, 2023. <https://india.unfpa.org/en/publications/india-ageing-report-2023>
2. India State-Level Disease Burden Initiative Collaborators, “Nations within a nation: variations in epidemiological transition across the states of India, 1990–2016 in the Global Burden of Disease Study”, *Lancet*, vol. 390, no. 10111, pp. 2437–2460, 2017. [https://doi.org/10.1016/S0140-6736\(17\)32804-0](https://doi.org/10.1016/S0140-6736(17)32804-0)

3. Skou S. T., Mair F. S., Fortin M., Guthrie B., Nunes B. P., Miranda J. J., et al., “Multimorbidity”, *Nat Rev Dis Primers*, vol. 8, art. 48, 2022. <https://doi.org/10.1038/s41572-022-00376-4>
4. Chowdhury S. R., Chandra Das D., Sunna T. C., Beyene J. and Hossain A., “Global and regional prevalence of multimorbidity in the adult population in community settings: a systematic review and meta-analysis”, *EClinicalMedicine*, vol. 57, art. 101860, 2023. <https://doi.org/10.1016/j.eclinm.2023.101860>
5. Barnett K., Mercer S. W., Norbury M., Watt G., Wyke S. and Guthrie B., “Epidemiology of multimorbidity and implications for health care, research, and medical education: a cross-sectional study”, *Lancet*, vol. 380, no. 9836, pp. 37–43, 2012. [https://doi.org/10.1016/S0140-6736\(12\)60240-2](https://doi.org/10.1016/S0140-6736(12)60240-2)
6. India State-Level Disease Burden Initiative Diabetes Collaborators, “The increasing burden of diabetes and variations among the states of India: the Global Burden of Disease Study 1990–2016”, *Lancet Glob Health*, vol. 6, no. 12, pp. e1352–e1362, 2018. [https://doi.org/10.1016/S2214-109X\(18\)30387-5](https://doi.org/10.1016/S2214-109X(18)30387-5)
7. Sarma P. S., Sadanandan R., Thulaseedharan J. V., Soman B., Srinivasan K., Varma R. P., et al., “Prevalence of risk factors of non-communicable diseases in Kerala, India: results of a cross-sectional study”, *BMJ Open*, vol. 9, no. 11, art. e027880, 2019. <https://doi.org/10.1136/bmjopen-2018-027880>
8. Patel P., Muhammad T. and Sahoo H., “The burden of disease-specific multimorbidity among older adults in India and its states: evidence from LASI”, *BMC Geriatr*, vol. 23, art. 53, 2023. <https://doi.org/10.1186/s12877-023-03728-1>
9. Khan M. R., Malik M. A., Akhtar S. N., Yadav S. and Patel R., “Multimorbidity and its associated risk factors among older adults in India”, *BMC Public Health*, vol. 22, art. 746, 2022. <https://doi.org/10.1186/s12889-022-13181-1>
10. Sinha A., Kerketta S., Ghosal S., Kanungo S., Lee J. T. and Pati S., “Multimorbidity and complex multimorbidity in India: findings from the 2017–2018 Longitudinal Ageing Study in India (LASI)”, *Int J Environ Res Public Health*, vol. 19, no. 15, art. 9091, 2022. <https://doi.org/10.3390/ijerph19159091>
11. Chauhan S., Patel R. and Kumar S., “Prevalence, factors and inequalities in chronic disease multimorbidity among older adults in India: analysis of cross-sectional data from the nationally representative Longitudinal Ageing Study in India (LASI)”, *BMJ Open*, vol. 12, no. 3, art. e053953, 2022. <https://doi.org/10.1136/bmjopen-2021-053953>
12. Chauhan S., Srivastava S., Kumar P. and Patel R., “Decomposing urban-rural differences in multimorbidity among older adults in India: a study based on LASI data”, *BMC Public Health*, vol. 22, art. 502, 2022. <https://doi.org/10.1186/s12889-022-12878-7>
13. Krishnamoorthy Y., Rajaa S., Verma M., Kakkar R. and Kalra S., “Spatial patterns and determinants of diabetes mellitus in Indian adult population”, *Diabetes Ther*, vol. 14, no. 1, art. 63, 2023. <https://doi.org/10.1007/s13300-022-01329-6>
14. Das P., Behera M. R., Das A., Behera D. and Khan J., “An exploratory assessment of geographic variation and disease clustering of multimorbidity among older adults in Odisha, India”, *Cureus*, vol. 18, no. 6, art. e110436, 2026. <https://doi.org/10.7759/cureus.110436>
15. Dolui M., Sarkar S., Hossain M. and Manna H., “Demographic and socioeconomic correlates of multimorbidity due to non-communicable diseases among adult men in India: evidence from the nationally representative survey (NFHS-5)”, *Clin Epidemiol Glob Health*, vol. 23, art. 101376, 2023. <https://doi.org/10.1016/j.cegh.2023.101376>
16. Diez-Roux A. V., “Bringing context back into epidemiology: variables and fallacies in multilevel analysis”, *Am J Public Health*, vol. 88, no. 2, pp. 216–222, 1998. <https://doi.org/10.2105/AJPH.88.2.216>
17. von Elm E., Altman D. G., Egger M., Pocock S. J., Gøtzsche P. C., Vandenbroucke J. P. and STROBE Initiative, “The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement: guidelines for reporting observational studies”, *Lancet*, vol. 370, no. 9596, pp. 1453–1457, 2007. [https://doi.org/10.1016/S0140-6736\(07\)61602-X](https://doi.org/10.1016/S0140-6736(07)61602-X)
18. Perianayagam A., Bloom D., Lee J., Parasuraman S., Sekher T. V., Mohanty S. K., et al., “Cohort profile: the Longitudinal Ageing Study in India (LASI)”, *Int J Epidemiol*, vol. 51, no. 4, pp. e167–e176, 2022. <https://doi.org/10.1093/ije/dyab266>

19. International Institute for Population Sciences (IIPS), National Programme for Health Care of Elderly (NPHCE), MoHFW, Harvard T.H. Chan School of Public Health (HSPH) and University of Southern California (USC), "Longitudinal Ageing Study in India (LASI) Wave 1, 2017–18, India Report", IIPS, Mumbai, 2020. <https://www.iipsindia.ac.in/>
20. Johnston M. C., Crilly M., Black C., Prescott G. J. and Mercer S. W., "Defining and measuring multimorbidity: a systematic review of systematic reviews", *Eur J Public Health*, vol. 29, no. 1, pp. 182–189, 2019. <https://doi.org/10.1093/eurpub/cky098>
21. Fortin M., Stewart M., Poitras M. E., Almirall J. and Maddocks H., "A systematic review of prevalence studies on multimorbidity: toward a more uniform methodology", *Ann Fam Med*, vol. 10, no. 2, pp. 142–151, 2012. <https://doi.org/10.1370/afm.1337>
22. Mohanty S. K., Abhilasha, Mishra R. S., Upadhyay A. K., O'Donnell O. and Maurer J., "Sociodemographic and geographic inequalities in diagnosis and treatment of older adults' chronic conditions in India: a nationally representative population-based study", *BMC Health Serv Res*, vol. 23, art. 332, 2023. <https://doi.org/10.1186/s12913-023-09318-6>
23. Katz S., Ford A. B., Moskowitz R. W., Jackson B. A. and Jaffe M. W., "Studies of illness in the aged: the index of ADL: a standardized measure of biological and psychosocial function", *JAMA*, vol. 185, no. 12, pp. 914–919, 1963. <https://doi.org/10.1001/jama.1963.03060120024016>
24. Lawton M. P. and Brody E. M., "Assessment of older people: self-maintaining and instrumental activities of daily living", *Gerontologist*, vol. 9, no. 3, pp. 179–186, 1969. https://doi.org/10.1093/geront/9.3_Part_1.179
25. Tobler W. R., "A computer movie simulating urban growth in the Detroit region", *Econ Geogr*, vol. 46, suppl., pp. 234–240, 1970. <https://doi.org/10.2307/143141>
26. Moran P. A. P., "Notes on continuous stochastic phenomena", *Biometrika*, vol. 37, no. 1/2, pp. 17–23, 1950. <https://doi.org/10.2307/2332142>
27. Anselin L., "Local indicators of spatial association – LISA", *Geogr Anal*, vol. 27, no. 2, pp. 93–115, 1995. <https://doi.org/10.1111/j.1538-4632.1995.tb00338.x>
28. Anselin L., Syabri I. and Kho Y., "GeoDa: an introduction to spatial data analysis", *Geogr Anal*, vol. 38, no. 1, pp. 5–22, 2006. <https://doi.org/10.1111/j.0016-7363.2005.00671.x>
29. Merlo J., Chaix B., Ohlsson H., Beckman A., Johnell K., Hjerpe P., et al., "A brief conceptual tutorial of multilevel analysis in social epidemiology: using measures of clustering in multilevel logistic regression to investigate contextual phenomena", *J Epidemiol Community Health*, vol. 60, no. 4, pp. 290–297, 2006. <https://doi.org/10.1136/jech.2004.029454>
30. Goldstein H., Browne W. and Rasbash J., "Partitioning variance in multilevel models", *Underst Stat*, vol. 1, no. 4, pp. 223–231, 2002. https://doi.org/10.1207/S15328031US0104_02
31. Larsen K. and Merlo J., "Appropriate assessment of neighborhood effects on individual health: integrating random and fixed effects in multilevel logistic regression", *Am J Epidemiol*, vol. 161, no. 1, pp. 81–88, 2005. <https://doi.org/10.1093/aje/kwi017>
32. Austin P. C. and Merlo J., "Intermediate and advanced topics in multilevel logistic regression analysis", *Stat Med*, vol. 36, no. 20, pp. 3257–3277, 2017. <https://doi.org/10.1002/sim.7336>
33. Self S. G. and Liang K. Y., "Asymptotic properties of maximum likelihood estimators and likelihood ratio tests under nonstandard conditions", *J Am Stat Assoc*, vol. 82, no. 398, pp. 605–610, 1987. <https://doi.org/10.1080/01621459.1987.10478472>
34. Maas C. J. M. and Hox J. J., "Sufficient sample sizes for multilevel modeling", *Methodology*, vol. 1, no. 3, pp. 86–92, 2005. <https://doi.org/10.1027/1614-2241.1.3.86>
35. Rabe-Hesketh S. and Skrondal A., "Multilevel modelling of complex survey data", *J R Stat Soc Ser A Stat Soc*, vol. 169, no. 4, pp. 805–827, 2006. <https://doi.org/10.1111/j.1467-985X.2006.00426.x>



36. Geldsetzer P., Manne-Goehler J., Theilmann M., Davies J. I., Awasthi A., Vollmer S., et al., "Diabetes and hypertension in India: a nationally representative study of 1.3 million adults", JAMA Intern Med, vol. 178, no. 3, pp. 363–372, 2018. <https://doi.org/10.1001/jamainternmed.2017.8094>
37. Ministry of Health and Family Welfare, Government of India, "National Programme for Prevention and Control of Non-Communicable Diseases (NP-NCD)", National Health Mission. <https://nhm.gov.in/>
38. Ministry of Health and Family Welfare, Government of India, "National Programme for Health Care of Elderly (NPHCE)", National Health Mission. <https://nhm.gov.in/>
39. National Health Authority, Government of India, "Ayushman Bharat Pradhan Mantri Jan Arogya Yojana (PM-JAY)". <https://pmjay.gov.in/>
40. Gateway to Global Aging Data, "Longitudinal Ageing Study in India (LASI) data and documentation". <https://g2aging.org/>