Healthcare-seeking behavior and spatial variation of internal migrants with chronic diseases: a nationwide empirical study in China

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Abstract

Individuals migrating with chronic diseases often face substantial health risks, and their patterns of healthcare-seeking behavior are commonly influenced by mobility. However, to our knowledge, no research has used spatial statistics to verify this phenomenon. Utilizing data from the China Migrant Dynamic Survey of 2017, we conducted a geostatistical analysis to identify clusters of chronic disease patients among China's internal migrants. Geographically weighted regressions were utilized to examine the driving factors behind the reasons why treatment was not sought by 711 individuals among a population sample of 9272 migrant people with chronic diseases. The results indicate that there is a spatial correlation in the clustering of internal migrants with chronic diseases in China. The prevalence is highly clustered in Zhejiang and Xinjiang in north-eastern China. Hotspots were found in the north-east (Jilin and Liaoning), the north (Hebei, Beijing, and Tianjin), and the east (Shandong) and also spread into surrounding provinces. The factors that affect the migrants with no treatment were found to be the number of hospital beds per thousand population, the *per capita* disposable income of medical care, and the number of participants receiving health education per 1000 Chinese population. To rectify this situation, the local government should "adapt measures to local conditions." Popularizing health education and coordinating the deployment of high-quality medical facilities and medical workers are effective measures to encourage migrants to seek reasonable medical treatment.

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Introduction

Migration is associated with an increased risk of chronic disease, especially obesity, diabetes, and cardiovascular diseases (Vandenheede *et al*., 2012). However, many previous studies have concentrated on preventing and treating infectious diseases, grounded in the belief that the large majority of the diseases affecting migrants were infectious or tropical ("exotic") in nature (Modesti *et al*., 2016), leading to the neglect of chronic diseases in these people. Early on, McKeigue *et al*. (1989) highlighted the increased risk of coronary heart disease among South Asian migrants to Europe. Echoing this, Adhikari and Sanou (2012) noted that non-white immigrants, especially from south Asia, the Caribbean, sub-Saharan Africa, and latin America, consistently face significantly increased diabetes burdens in comparison with Canadian immigrants. Testa *et al*. (2016) further indicate that immigrants in European countries, notably those with type 2 diabetes, face higher risks of mortality and morbidity than their European counterparts. Remarkably, about half of recent Mexican immigrants to the United States with diabetes were unaware of their condition, representing an undiagnosed prevalence rate 2.3 times greater than that observed among Mexican Americans with similar demographic profiles (Barcellos *et al.,* 2012). This pattern highlights the widespread difficulties in managing and diagnosing chronic diseases among immigrant populations worldwide. Recognizing the additional complexities that migrant communities introduce is crucial for strengthening health systems' capacity to improve population health. Since the reform and opening-up in China, there has been a substantial rise in the magnitude of internal migration, driven by the pursuit of enhanced employment and educational opportunities. According to the seventh national census bulletin (No. 7), published by the National Bureau of Statistics, as of November 2020, China's internal migrant population reached 375,816,759, *i.e*., 26.65% of the total population (National Bureau of Statistics, 2021). This marked a significant increase of 69.73% from the figures reported in the sixth census of 2010 (National Bureau of Statistics, 2021). As the aged population continues to grow, the impact of unhealthy lifestyles and the prevalence of chronic diseases among the migrant population are also significantly increasing (He *et al.,* 2022). Migrants primarily engage in physical labor in the non-farming income sector, often in industries characterized by high labor intensity, increased risk factors, and a greater incidence of occupational diseases (Yao & Zhao, 2015). Furthermore, many of them have unhealthy lifestyles, including a relatively high prevalence of tobacco smoking, excessive alcohol consumption, insufficient intake of vegetables and fruit, and physical inactivity, all of which can lead to chronic diseases (Chen *et al*., 2017). Therefore, a series of targeted measures must be proposed for migrants with chronic diseases (MCDs) to improve this situation. Chronic diseases often demand prolonged medication, so the "notice from the Office of the National Social Security Administration on further improving the management of designated retail inclusion in outpatient coordination" released on February 15, 2023, was welcome. This notice specifies that expenses incurred by insured individuals for medications listed in the medical insurance directory, purchased at designated retail pharmacies with a prescription from designated medical institutions, can be covered by the pooled fund according to the regulations (State Council of the People's Republic of China, 2023). Several studies have confirmed that the utilization level of MCD medical services in China is insufficient and pointed out that the factors influencing their healthcare-seeking behavior are related to gender, age, ethnic group, household registration type, area of residence, the establishment of health records, receiving health education for chronic diseases, and the time required to move from the place of residence to the nearest medical service institution (Song & Zhang, 2021; He *et al*., 2022). However, these investigations primarily focus on individual heterogeneity, lack of broader examination of macro-level influences, and overlook significant regional disparities.

The factors influencing health outcomes and healthcare-seeking behaviors are multifaceted, with micro factors (such as demographic factors) directly impacting health outcomes while macro factors (such as regional social development level and medical and health level) indirectly impacting health outcomes (Guo, 2021). Moreover, the role of social determinants in health, focusing on structural elements beyond medical care and influenced by socioeconomic policies and inequalities, significantly affects health outcomes (Braveman *et al.,* 2011; Castañeda *et al*., 2015).

Geographic information systems (GIS) assist in effectively analyzing the spatial attributes of data, which is widely used to explore the spatial distribution characteristics of health (Xiang *et al*., 2023). GIS offer crucial data support for devising regional strategies for the prevention and control of chronic disease. Geographically weighted regression (GWR) is a spatial analysis technique that can explore the spatial distribution of MCDs and their associated drivers by establishing local regression equations at each point in the spatial range. Due to the consideration of the local effects of space objects, it has the advantage of high accuracy. Consequently, this study seeks to analyze the regional distribution and health-seeking behaviors of MCDs, explore the geographical dimension's factors of influence on healthcare-seeking behavior, and provide crucial insights for formulating region-specific prevention and control strategies for chronic diseases among migrant populations. To delve deeper into the factors contributing to higher disease incidence in certain areas, we analyzed the particular migration patterns crossing provincial borders in Heilongjiang, Inner Mongolia, Sichuan, Zhejiang, and Xinjiang. The research process followed the scheme shown in Figure 1.

Materials and Methods

Data source

The data originated from the China Migrant Dynamic Survey 2017 (CMDS, 2017), conducted by the former National Health and Family Planning Commission, using a stratified, multi-stage sampling method of probability proportionate to size. The national survey's basic sampling frame encompassed all 31 provinces in China (autonomous regions and municipalities directly under the Central Government, including the Xinjiang Production and Construction Corps but excluding the Hong Kong Special Administrative Region, the Macao Special Administrative Region, and Taiwan Province). The collected sample size comprised 169,989 individuals targeting the migrant population aged 15 years and above residing in the inflow area for more than one month but not registered in the local area (city, county).

Firstly, the study extracted the responses to Q406 in the questionnaire, which asks, "have you ever been diagnosed with high blood pressure (HBP) or diabetes mellitus (DM) by a doctor?" and selected samples from those who chose "suffering from HBP" and "suffering from DM" as well as from those who chose "suffering from HBP and DM (HBP&DM)". This process yielded 9272 (5.5%) valid samples, comprising 7182 with HBP, 1182 with DM, and 908 with both HBP and DM. Additionally, 3837 respondents (2.6%) did not seek medical treatment, indicating they might have chronic diseases of which they are unaware.

Secondly, we noted the responses to question Q410, which asked "do you have an illness (injury) or physical discomfort in the last year?", which identified 5657 positive answers that were followed up by question Q411: "where did you seek care when you first felt ill, experienced an injury or felt unwell?". This inquiry uncovered seven distinct healthcare-seeking behavior patterns. For detailed descriptions and participant numbers see Table 1. 711 samples did not take any treatment measures after the illness. According to behavioral economics' prospect theory, opting for no treatment or self-treatment reflects an inadequate perception of disease risk, representing a highly irrational healthcare-seeking behavior that is a risk preference towards potential health loss. Naturally, this behavior leads to treatment delays, which adversely affect the person's health. We studied this tendency to explore the driving factors that affect the proportion of no-treatment migrants in relation to the total investigated migrants (NT-ratio) in each province.

Selection of study variables

We drew upon the contextual characteristics dimension of Andersen and Davidson's (2014) behavioral model of health services use (BMHSU). BMHSU is a widely recognized model in the field of medical sociology and health service research for examining the factors influencing individual healthcare behaviors and access to medical services. Considering the distinct migration features of China's internal migrants, such as household registration status, mobility scope/type, and family economic standing, based on the previous research (Gu *et al.,* 2020; Zhang *et al.,* 2021; Wang *et al.,* 2022), we incorporated migrant-specific factors outside the model that could potentially affect the healthcare-seeking behavior of MCDs. According to data availability, a total of 18 explanatory variables were obtained as shown in Table 2.

Spatial autocorrelation analysis

Using the local spatial autocorrelation analysis in GeoDa 1.22 software, we separately plotted the Moran scatter diagrams for HBP, DM, and HBP&DM. This refers to the potential interdependence of some variables in the same distribution area. Its fundamental starting point is Tobler's first law of geography (Tobler, 1970). It commonly uses Moran's I and Geary's C index (Geary, 1954) to explain space relations. Compared with Geary's C index, Moran's I is not easily affected by the deviation from the normal distribution. We used Moran's I to explore the spatial autocorrelation of

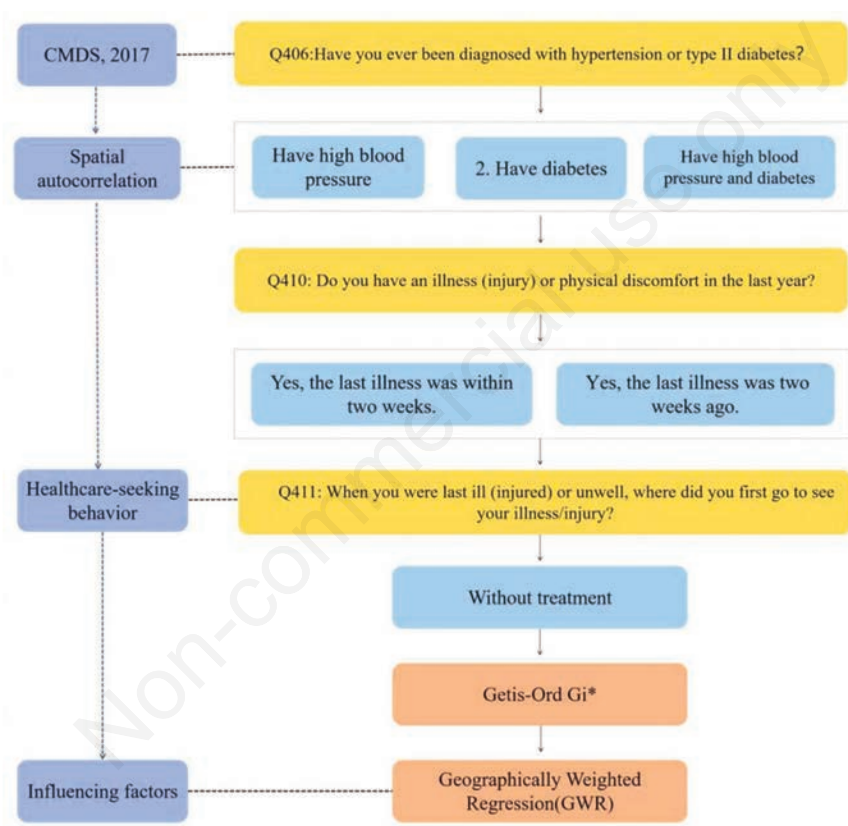

Figure 1. Research process. CMDS, China Migrant Dynamic Survey.

Table 1. Distribution of healthcare-seeking by migrants in the study group.

Place chosen to visit	Number	Proportion (%)
Local community (sub-district) public health	1068	18.9
Local private clinic	857	15.2
Local general/specialist hospital	1318	23.3
Local pharmacy	1582	27.97
Returned to hometown for treatment	78	1.4
Treatment in a place other than hometown	43	0.8
None (no treatment)	711	12.6

the prevalence of HBP, DM, and HBP&DM of migrants in each province. Global Moran's *I* measures the average spatial autocorrelation based on both feature locations and feature values simultaneously, while local Moran's *I* and local indicators of spatial association (LISA) (Anselin, 1995) represent an implementation of Moran's *I* for each location (observation). Together, these approaches measure the overall prevalence rate of unit spatial autocorrelation in neighboring provinces and the degree of spatial correlation and spatial difference between each province and its neighboring ones. Equation 1 expresses global Moran's *I*:

$$Moran'sI = \frac{\sum_{i=1}^{n}\sum_{i=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \qquad \text{(Eq. 1)}$$

where x_i and x_j are the observed values of the proportion of MCDs in province *i* and *j*; *n* the number of provinces; and w_{ij} the spatial weight matrix reflecting whether province *i* and province *j* are spatially adjacent. If in this case Moran's $I>0$, there is a positive spatial correlation, that is, areas with high or low occurrences tend to be clustered in space. Values <0 indicate a negative spatial correlation, that is areas with high and low occurrences tend to be spatially discrete. For the i^{th} province, the local Moran index I_i is calculated as in equation 2:

$$I_i = \frac{(x_i-\bar{x})}{S^2}\sum_{j=1,j\neq 1}^{n} w_{ij}(x_j-\bar{x}) \qquad \text{(Eq. 2)}$$

The LISA cluster map displays the four local spatial association cluster types determined by Moran's regular distribution significance test for spatial distribution. Based on the positive or negative values of I_i, the local spatial association zones can be divided into two categories: when $I_i>0$, there is a positive correlation in local space, which includes the so called high-high clusters (HHs) and low-low clusters (LLs); when $I_i<0$, the correlation in local space is negative, but it still includes HH and LL clusters (Cui *et al*., 2022). The former indicates that the attribute values of the regional units and their neighbors are high; these units are hotspots, while the latter indicates that the attribute values of the regional units and their neighbors are low, *i.e*., coldspots. The space units in the first and third quadrants have a strong positive space correlation. HL indicates that an attribute value of a regional unit is high, whereas the attribute values of its neighbors are low. LH is the opposite, *i.e.*, the spatial units in the second and fourth quadrants have a strong negative correlation.

Hotspot analysis

The cluster and dispersion of spatial objects can be shown by Getis-Ord Gi*. Moran's *I* index can reflect the overall distribution of spatial objects. However, it is difficult to reflect the extent of the clustering and dispersion in space. Since the interference of the space is heterogeneous, the overall correlation of spatial objects is also not certain in the actual distribution. It is necessary to analyze the statistical significance in partial space based on Getis-Ord Gi* (Yang *et al*., 2020). On this foundation, we used Getis-Ord Gi* statistics (Getis & Ord, 1992) to identify outbreak areas (hotspots) of NT-ratio. The local Getis-Ord Gi* statistics are expressed in equations 3-5:

$$Gi^* = \frac{\sum_{j=1}^{n} w_{ij}x_j - \bar{X}\sum_{j=1}^{n} w_{ij}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{ij}^{2} - \left(\sum_{j=1}^{n} w_{ij}\right)^2\right]}{n-1}}} \qquad \text{(Eq. 3)}$$

Table 2. Variables and expected effects.

Type	Variable	Explication
Healthcare-seeking behavior	NT-ratio	Proportion of MCDs in needed to see a doctor but neither did do nor take any treatment
Demography	Age	Average MCDs' age in each province (given as year reached after birth)
	Sex	Percentage the males and the females of the MCDs
	Marital status	Percentage proportions of the MCDs who were married
	Schooling	Average number of years of schooling of the MCDs
Socioeconomy	CD	Per capita disposable income for each provinces (CNY)
	Income used for HDI	Per capita income used for healthcare in each province (CNY)
	THE	Average per capita expenditure per visit for medical care (CNY)
	IE ratio	Percentage proportion of the family income to the average expenditure
	MICRUE	Percentage coverage rate of medical insurance for urban employees in each province
Hospitalization	NGP	Number of general practitioners per thousand population in each province (people)
	NH	Number of hospitals per thousand population in each province
	NHB	Number of hospital beds per thousand population in each province
Health indices	Mortality rate	Percentage mortality rate by province
	Life expectancy	Average life expectancy by number of years in each province
	SRH	Mean value of self-rated health index of MCDs
General environmental data	HT	Percentage proportion of MCDs living in a house they had purchased themselves
	Trans-provincial movers	Percentage proportion of MCDs who had migrated from one province to another
	Health education (HE)	Number of participants in health education per 1000 population

CD, per capita disposable income; IE-ratio, proportion of the family income to the average expenditure; HDI, per capita healthcare disposable income; HT, housing type; MCD, migrants with chronic diseases; MICRUE, medical insurance coverage rate of medical insurance for urban employees; NGP, number of general practitioners per thousand population; NH, number of hospitals per thousand population; NHB, number of hospital beds per thousand population; NT-ratio, the proportion of no-treatment migrants in relation to the total investigated migrants; CNY, China Yuan; THE, total health expenditure; SRH, self-rated health index, based on questionnaire Q401: "How is your health?" A1. Health, A2.Essential health, A3. Unhealthy but able to care for myself, A4. Cannot care for myself. This study calculated the average self-rated health of the MCDs in each province, and the smaller the index, the better the health status.

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \quad \text{(Eq. 4)}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2} \quad \text{(Eq. 5)}$$

where x_j is the attribute value of factor j; w_{ij} is the space weight between elements i and j; and n is the total number of elements. Gi* represents the statistical significance and mirrors the degree of clustering and dispersion. The higher it is, the more clustered the high values are (hotspots); the lower, the more clustered the low values are (coldspots).

Spatial regression analysis

The potential factors influencing the NT-ratio of MCDs were analyzed using the GWR analysis function in ArcMap 10.8.1 (ESRI, Redlands, CA, USA). In previous studies, the impact analysis on the healthcare-seeking behavior of migrants is mainly based on the traditional ordinary least squares (OLS) model. However, this model implies the assumption of spatial homogeneity, that is, the regression coefficients of each sample point are equal. Suppose there is spatial non-stationarity in the relationship between independent variables and dependent variables at each sample point, then the global regression model represented by OLS model cannot measure the differentiated impacts of independent variables in different regions on dependent variables (Charlton *et al*., 2002; Fotheringham *et al*., 2013). Therefore, we studied the spatial variation characteristics of the factors affecting the proportion of MCDs based on the GWR, a statistical technique for spatial data analysis, particularly when the data exhibits heterogeneity (*i.e*., the statistical properties of the data vary across different geographical locations). GWR has widespread applications in the field of public health, especially in epidemiology (Oshan *et al.*, 2020), in environmental health assessment (Jephcote *et al.,* 2012) and in the spatial distribution of health services (Feng *et al.,* 2017). By accounting for spatial heterogeneity, GWR enables researchers to analyze the geographic variation more accurately in health outcomes in relation to environmental factors, and socioeconomic status. GWR allows model parameters to vary spatially, thereby capturing and explaining spatial variability. In these models, the corrected Akaike Information Criterion (AICc) is used to determine the optimal bandwidth size, ensuring the model accurately reflects the spatial characteristics of the data while avoiding overfitting.

Since the sample areas selected by China Migrant Dynamic Survey data are provinces, the sample areas of each province can be approximately simplified into points for coordinate sub-collection when studying the national scale problem (Gu *et al.,* 2020). The GWR model is formulated as in equation 6:

$$\gamma_i = \beta_0(\mu_i,\nu_i) + \beta_1(\mu_i,\nu_i)x_{i1} + \beta_2(\mu_i,\nu_i)x_{i2} + \ldots + \beta_n(\mu_i,\nu_i)x_{in} + \varepsilon_{i,} \quad \text{(Eq. 6)}$$

where (μ_i,ν_i) represents the geographical location of sample point i, which can represent the projected coordinate system or geographical coordinates x_{i1}, x_{i2}, ...; x_{in} the characteristic variables β_1 (μ_i, ν_i), $\beta_1(\mu_i,\nu_i)$, $\beta_2(\mu_i,\nu_i)$,...; $\beta_n(\mu_i,\nu_i)$ the regression coefficient of x_{i1}, x_{i2},... x_{in}; with the regression coefficient of x_{in} calculated as in equation 7

$$\hat{\beta}(u_i,v_i) = \left[X^T W(u_i,v_i) X\right]^{-1} X^T W(u_i,v_i) Y \quad \text{(Eq. 7)}$$

where $W(\mu_i,v_i)$ is the spatial weight matrix; W_{ij} the spatial weight of sample i to sample j, which is calculated by the Gaussian function expressed in equation 8:

$$w_{ij} = e^{-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2} \quad \text{(Eq. 8)}$$

where d_{ij} is the metric distance between sample point j and sample point i; and b is the bandwidth.

In this paper, the AICc was adopted to determine the bandwidth, with the minimum AICc selected as the most adaptive bandwidth. The formula is expressed in equation 9:

$$AICc = 2n\ln(\sigma) + n\ln(2\pi) + n\frac{n+\mathrm{tr}(S)}{n-2-\mathrm{tr}(S)} \quad \text{(Eq. 9)}$$

where n is the number of sample points; σ the standard deviation of the error estimation term; and tr(S) is the S-matrix trace of GWR.

In this study, the GWR analysis includes key statistical parameters: t-value (t-statistic), regression coefficient (b, coefficient), adjusted t-value (robust-t), and adjusted regression coefficient (robust-b). The t-value assesses the statistical significance of each coefficient. The regression coefficient measures the impact of an independent variable on the dependent variable, adjusted for location. Robust-t and robust-b are designed to provide a more robust test of statistical significance, particularly suitable for handling outliers or other factors that might violate the assumptions of the standard regression model.

Results

Descriptive demographic statistics

The prevalence of HBP among men was found to exceed that among women, with DM also more common in men than in women. We noted that the incidence of co-morbidity among men surpassed that among women, with the prevalence in men almost 1.5 times that of women on average. The MCD age profile included mainly 40-year-olds and over, with a focus on the 40~60-year-old group (quasi-elderly). The overall educational degree was found to be below junior high school, accounting for more than half of the study subjects. Table 3 provides the details.

Geographical distribution

MCDs were found to be highly prevalent in the Heilongjiang province and Inner Mongolia province. Table 4 presents the MCD prevalence rates of HBP, DM, and HBP&DM in each province (region) of China. Notably, Inner Mongolia, Heilongjiang, and Zhejiang reported the highest proportion of HBP, while Inner Mongolia, Sichuan, and Heilongjiang had the highest prevalence of DM. The regions with the highest proportion of HBP&DM were

Inner Mongolia, Heilongjiang, and Xinjiang. Generally, lower disease prevalence was seen in the eastern regions compared to the western ones, with rates diminishing from the north-east and north-west towards the south-east, as shown in Figure 2. The results indicate a significant prevalence of trans-provincial migration among MCD cases in Heilongjiang, Inner Mongolia, and Sichuan, with inter-provincial migrants constituting only 15.8%, 15.3%, and 15.8%, respectively. In contrast, the majority of MCD cases in Zhejiang and Xinjiang were related to inflow from other provinces, amounting to 83.3% and 65.2%, respectively. This suggests that Zhejiang and Xinjiang should prioritize medical and healthcare services for incoming populations, particularly hypertension care.

Autocorrelation

Moran's *I* values were 0.643, 0.319, and 0.598 for HBP, DM and HBP&DM, respectively, indicating a positive spatial correlation among these problems (Figure 3). Furthermore, most points in the Moran scatter plots were distributed in the first and third quadrants, demonstrating a high correlation between the prevalence of each disease and the geographical location of the migrants.

The separate analyses on the spatial clustering locations of migrants afflicted by HBP, DM and HBP&DM are shown in Figure 4. The local spatial autocorrelation analysis showed that migrants with HBP tend to form HH clusters in the north-east (Heilongjiang, Jilin, Liaoning) as well as in Inner Mongolia and Gansu, indicating higher incidences in these areas. Conversely, LL clusters, signifying lower disease prevalence, were found in Guangxi, Guangdong, Fujian, Hunan, Jiangxi, and Anhui. The spatial clustering of HBP&DM generally followed this trend. DM was characterized by HH clustering in Liaoning, with LL clustering in Shandong, Jiangsu, Anhui, Zhejiang, Jiangxi, Fujian, Guangdong, and Hubei. These results emphasize the importance of targeted public health interventions and policies to address the specific needs of migrants in different provinces.

Using Monte Carlo simulations to test Moran's *I* of the GeoDa results showed p-values at the 0.0010 level, both for HBP and HBP&DM indicating that the spatial autocorrelation was at the 99.9% confidence level was significant (Figure 5). For DM, the p-value was equal to 0.0030 indicating that the spatial autocorrelation was significant at the 99.7% confidence level (Figure 5).

Cluster analysis

The analysis revealed regions of high-value clusters (hotspots), low-value clusters (coldspots) and random values (not significant) (Figure 6). Notably, NT-ratio hotspots were prevalent in north-eastern China (Jilin and Liaoning), in the north (Hebei, Beijing, Tianjin) and in the East (Shandong), extending into adjacent provinces. Conversely, coldspots were found in north-west (Qinghai), south-west (Tibet and Sichuan) and south-central China (Guangxi, Guangdong and Fujian), suggesting a general trend of

Table 3. Descriptive demographic statistics of migrants with chronic diseases.

Demographic indicator	Population (%)	HBP (%)	DM (%)	HBP&DM (%)
Total number of study subjects	9272 (100)	7182 (77.5)	1182 (12.8)	908 (9.79)
Gender				
Men	5482 (58.9)	4270 (59.5)	711 (60.2)	501 (55.2)
Women	3790 (41.0)	2912 (40.6)	471 (38.9)	407 (44.8)
Age				
16-20 years	25 (0.3)	14 (0.2)	3 (0.3)	8 (0.9)
21-30 years	319 (3.4)	223 (3.1)	40 (3.4)	56 (6.2)
31-40 years	1208 (13.0)	938 (13.1)	172 (14.6)	98 (10.8)
41-50 years	3,193 (34.3)	2558 (35.6)	423 (35.9)	212 (23.4)
51-60 years	2450 (26.4)	1928 (26.8)	300 (25.4)	222 (24.5)
60＋years	2077 (22.3)	1521 (21.2)	244 (20.6)	312 (34.4)
Education				
Never attend any school	816 (8.8)	631 (8.8)	95 (8.0)	90 (9.9)
Primary school	2587 (27.9)	2007 (27.9)	332 (28.1)	248 (27.3)
Junior middle school	3701 (39.9)	2898 (40.4)	479 (40.5)	324 (35.7)
High school/ technical school	1499 (16.1)	1164 (16.2)	178 (15.1)	157 (17.3)
Junior college and above	669 (7.2)	482 (6.7)	98 (8.3)	89 (9.8)

HBP, high blood pressure; DM, diabetes mellitus.

Table 4. The prevalence of migrants with chronic diseases in province/autonomous regions.

Province	Total	HBP	Proportion (%)	DM	Proportion (%)	HBP&DM	Proportion (%)
Anhui	5000	209	4.18	15	0.30	18	0.36
Beijing	6999	278	3.97	71	1.01	38	0.54
Chongqing	6999	240	3.43	47	0.67	39	0.56
Fujian	4000	163	4.08	29	0.73	8	0.20
Gansu	9998	199	1.99	19	0.19	25	0.25
Guangdong	4999	222	4.44	42	0.84	17	0.34
Guangxi	5000	111	2.22	20	0.40	18	0.36
Guizhou	4000	210	5.25	39	0.98	21	0.53
Hainan	4999	105	2.10	13	0.26	11	0.22
Hebei	4999	206	4.12	26	0.52	25	0.50
Heilongjiang	4000	**297**	**7.43**	**45**	**1.13**	**44**	**1.10**
Henan	5000	176	3.52	19	0.38	24	0.48
Hubei	5000	197	3.94	26	0.52	28	0.56
Hunan	4000	184	4.60	30	0.75	19	0.48
Jiangsu	8000	384	4.80	45	0.56	22	0.28
Jiangxi	4000	125	3.13	18	0.45	10	0.25
Jilin	5000	284	5.68	30	0.60	49	0.98
Liangning	5000	289	5.78	50	1.00	41	0.82
Inner Mongolia	4000	**418**	**10.45**	**57**	**1.43**	**67**	**1.68**
Ningxia	4000	201	5.03	42	1.05	20	0.50
Qinghai	6000	179	2.98	38	0.63	22	0.37
Shaanci	5000	200	4.00	39	0.78	24	0.48
Shandong	5000	154	3.08	29	0.58	16	0.32
Shanghai	7000	307	4.39	47	0.67	53	0.76
Shanxi	5000	295	5.90	51	1.02	38	0.76
Sichuan	5000	237	4.74	**67**	**1.34**	37	0.74
Tianjin	3997	208	5.20	41	1.03	27	0.68
Xinjiang	7000	406	5.80	78	1.11	**73**	**1.04**
Xizang	6000	165	2.75	25	0.42	14	0.23
Yunnan	10000	191	1.91	35	0.35	27	0.27
Zhejiang	4999	**342**	**6.84**	49	0.98	33	0.66

DM, diabetes mellitus; HBP, high blood pressure. Provinces with high prevalence are in bold.

Table 5. Overall results of ordinary least squares and geographically weighted regression models with the no-treatment-ratio of the migrants with chronic diseases as the dependent variable.

Independent variable	OLS		GWR		
	t	*b*	Robust-*t*	Robust-*b*	VIF
NH	0.992745	0.330740	0.780906	0.442494	1.337778
NGP	-0.575318	0.5700430	-0.853395	0.401879	2.315766
NHB	-2.11724	0.044794*	-2.232478	0.035175*	1.278586
HDI	3.632995	0.001324**	1.487102	0.000152***	2.218870
HE	-1.797836	0.084794*	-1.754084	0.000006***	1.011479
R2	0.6548		0.6782		
Adj R2	0.5920		0.6257		
AICc	-88.642584		-93.881326		

*OLS, ordinary least squares; GWR, geographically weighted regression; t, t-value; b, regression coefficient; robust-t, adjusted t-value; robust-b, adjusted regression coefficient; VIF, variance inflation factor; HDI, per capita healthcare disposable income; NH, number of hospitals per thousand population; NGP, number of general practitioners per thousand population; NHB, number of hospital beds per thousand population; HE, number of health education participants per thousand population; R^2, coefficient of determination; adj. R^2, adjusted coefficient of determination; AICc, corrected Akaike Information Criterion; ***p<0.001; **p<0.01; *p<0.05.*

decreasing NT-ratio from the north-east to the south-west. The NT-ratios in the remaining 12 provinces were statistically non-significant.

Regression analysis

After addressing model collinearity and excluding factors with variance inflation factors exceeding 7.5, the model encompassed five factors: i) number of health education participants per 1000 population (HE); ii) number of general practitioners per 1000 population; iii) number of hospital beds per 1000 population (NHB); iv) number of hospitals per 1000 population (NH); v) *per capita* health care disposable income (HDI). The analysis revealed that NHB, HDI, and HE influenced the NT-ratio significantly (Table 5). HDI impacted the NT-ratio negatively, with this effect becoming more pronounced from the south-west to the north-east (Figure 7a), suggesting a correlation between fewer hospital beds and a greater likelihood of individuals with MCDs foregoing treatment. NHB impacted the NT-ratio positively, with this effect intensifying from the east to the west (Figure 7b). This indicates that increases

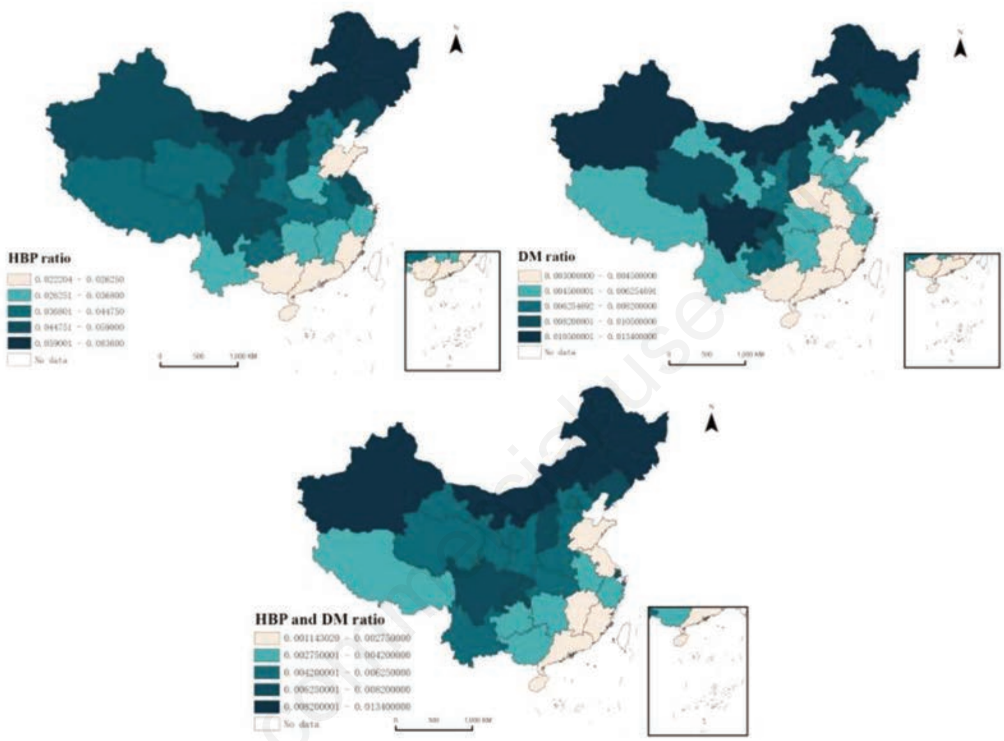

Figure 2. Provincial distribution of high blood pressure (HBP), diabetes mellitus (DM) and both simultaneously.

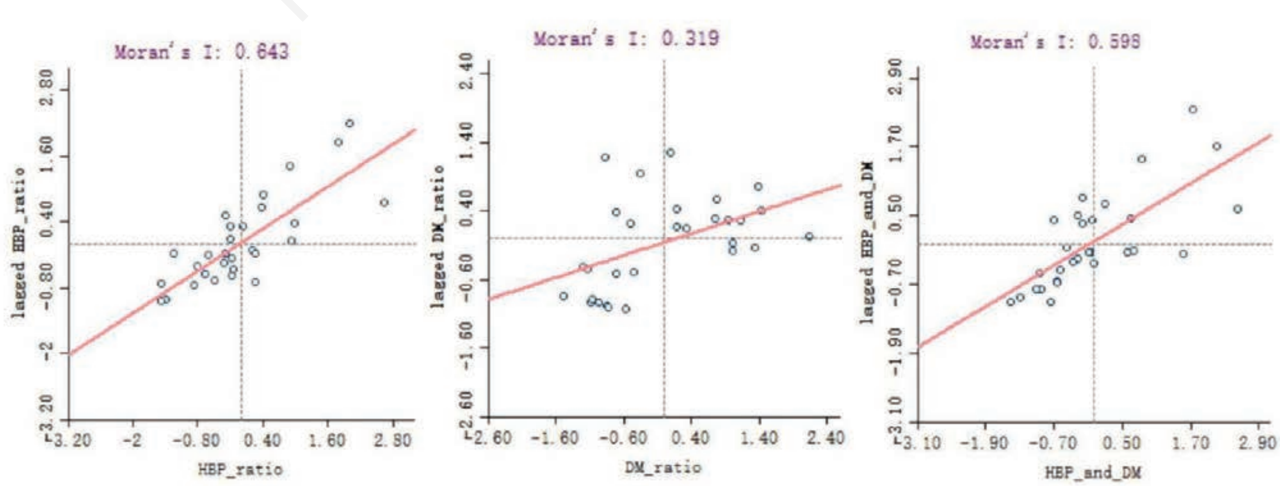

Figure 3. Moran scatter plots of the presence of high blood pressure (HBP), diabetes mellitus (DM) and both simultaneously.

in regional healthcare spending have not improved treatment access for MCDs, particularly not in Xinjiang. HE impacted the NT-ratio negatively, with influence growing from the north-west and south to the north-east (Figure 7c), implying that regional health education initiatives can effectively guide migrants to seek appropriate medical care, reducing the possibility of no treatment after their illness, particularly with the most notable effects observed in Heilongjiang and Jilin. In terms of the number of people participating in health education per 1000 population (HE popularizing rate) in each province, Gansu (9.779), Ningxia (7.193), and Qinghai (2.13) are the highest, with Jiangsu (0.181), Fujian (0.26) and Tianjin (0.279) the worse. The HE popularizing rate is calculated by dividing the number of health education training sessions attended by the year-end total population of each province, as sourced from the Disease Control and Public Health Services Statistics section of the China Health and Family Planning Statistical Yearbook 2017. The HE popularizing rate in Gansu is 54 times higher than that in Jiangsu, where it is the lowest.

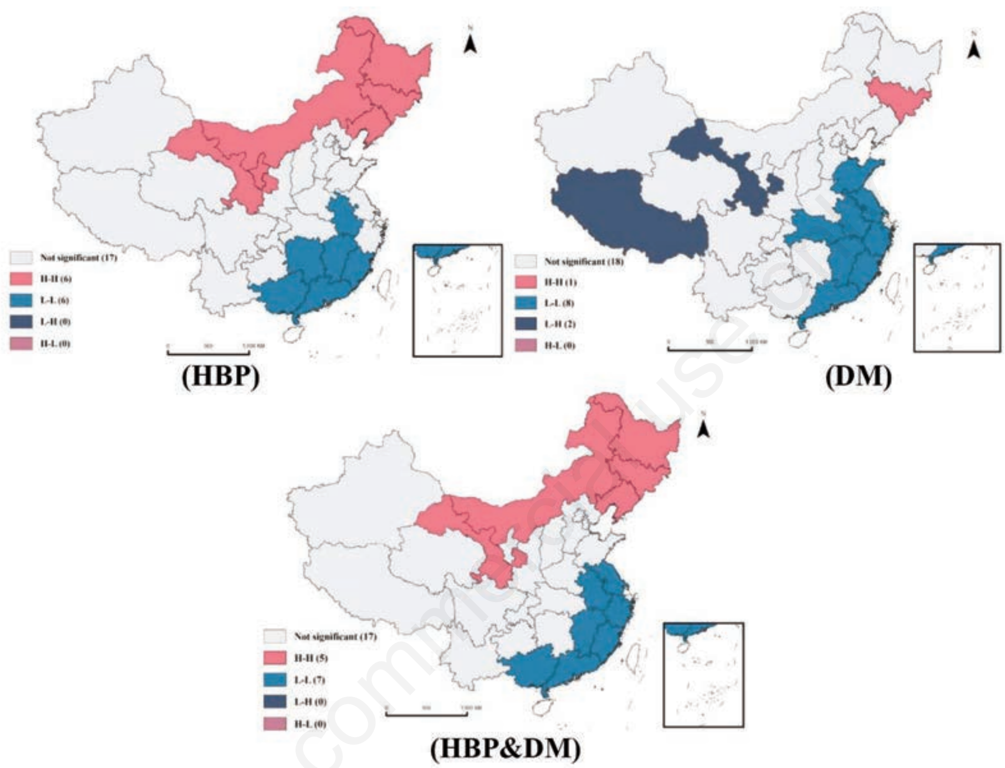

Figure 4. Agglomeration of local indicators of spatial association of high blood pressure (HBP), diabetes mellitus (DM) and both simultaneously (HBP&DM). H-H, high-high clusters; L-L, low-low clusters; L-H, low-high clusters; H-L, high-low clusters.

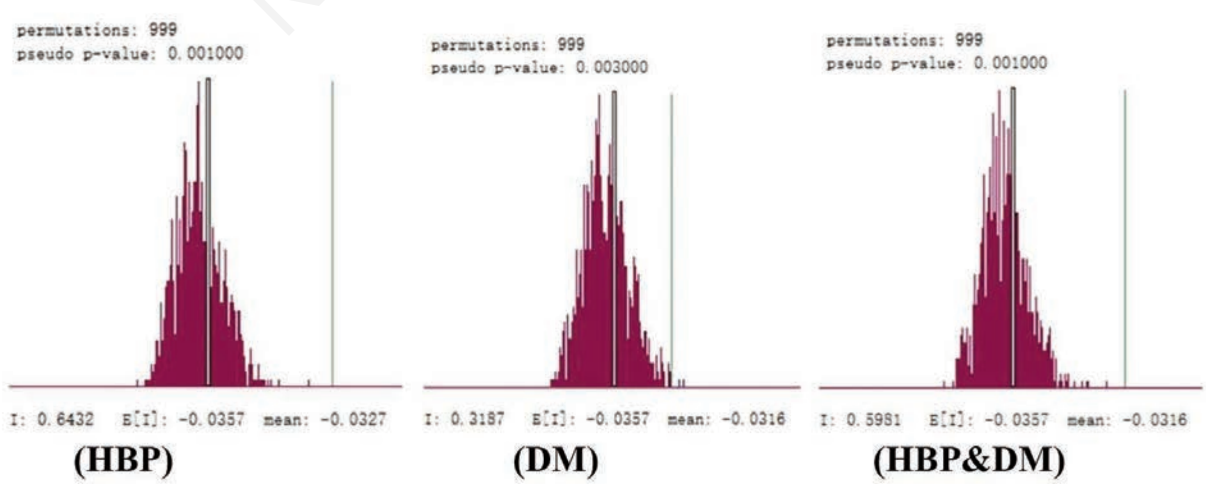

Figure 5. Monte Carlo test result of high blood pressure (HBP), diabetes mellitus (DM) and both simultaneously (HBP&DM).

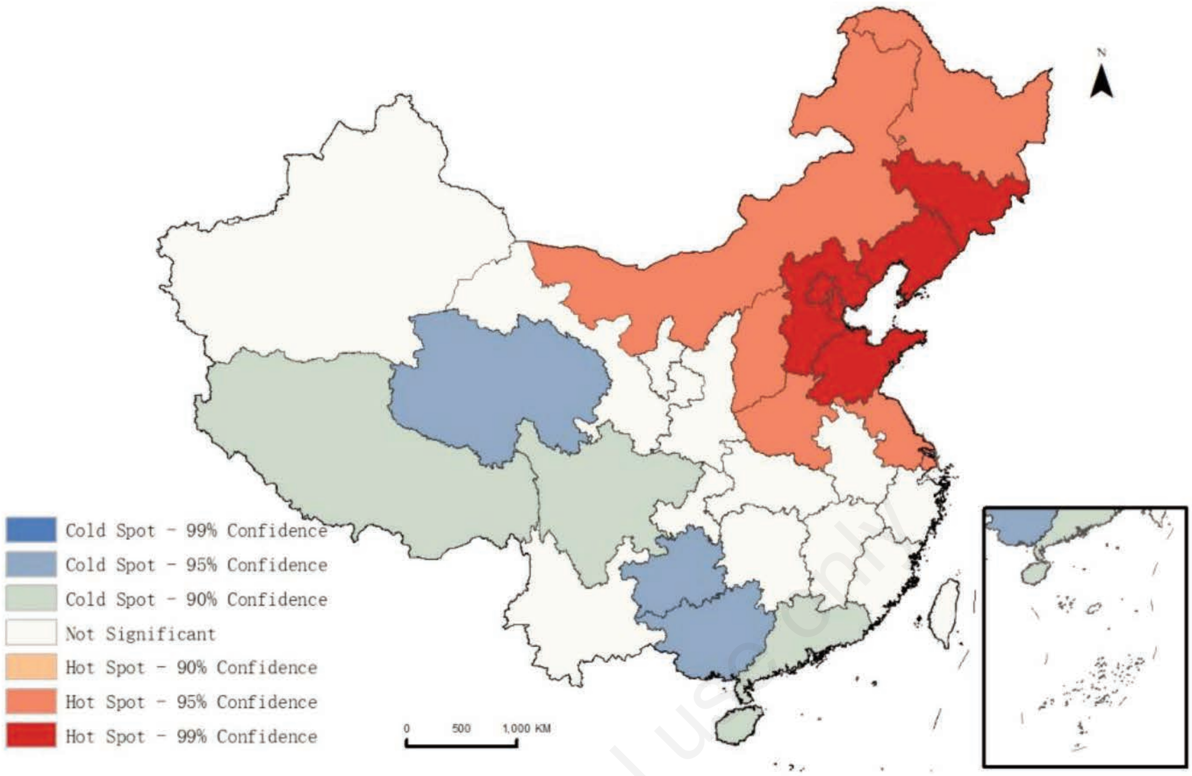

Figure 6. Spatial pattern of coldspots and hotspots with respect to the proportion of migrants not having sought treatment after falling ill in relation to the total number of investigated migrants (the no-treatment-ratio).

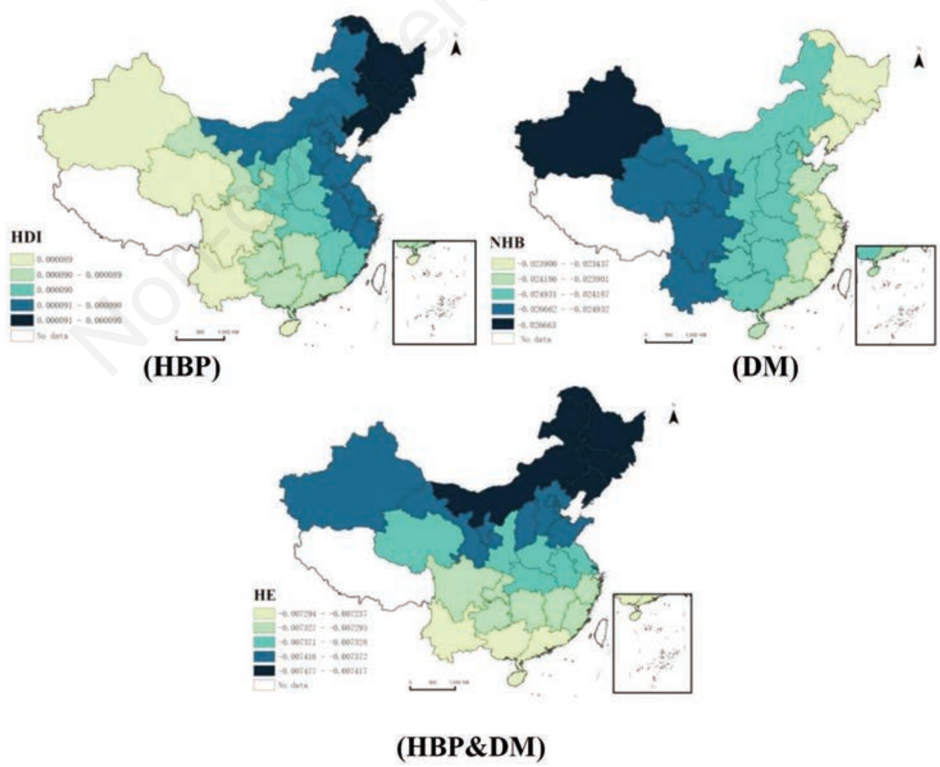

Figure 7. Spatial patterns of factors influencing the proportion of migrants not having sought treatment after falling ill in relation to the total number of investigated migrants (the no-treatment-ratio). HDI, *per capita* healthcare disposable income; NHB, number of hospital beds per thousand population; HE, number of health education participants per thousand population; HBP, high blood pressure; DM, diabetes mellitus.

Discussion

Prevalence and regional distribution of migrants with chronic diseases

The climate influences the prevalence of chronic diseases among migrants, leading to variable economic development levels and changing dietary habits when people move. To some extent, it is also affected by neighboring areas. The differences in Moran's *I* (HBP-ratio>DM&HBP-ratio>DM-ratio) suggest that the national unified chronic disease care and prevention policy cannot solve the differences in MCDs among provinces caused by spatial differences. It is necessary for each province/region to focus on the care and prevention of chronic diseases among local migrants. Special measures should be formulated based on the number of migrants, their age distribution, and the types of chronic diseases present.

HBP was the main disease in MCDs, accounting for 77.5% (7182/9272). The province with the highest proportion is Inner Mongolia, with Heilongjiang and Zhejiang following. Prior studies revealed that the detection rate of HBP is lower in low-altitude regions compared to high-altitude ones. Moreover, the incidence of HBP among China's ethnic minorities, such as Tibetans and Mongolians, was seen to significantly exceed that of the Han population (Zhang *et al.,* 2021). This suggests that factors including geography, climate, ethnicity, local dietary habits, and genetics play a critical role in the prevalence of chronic diseases like HBP. Accordingly, it is vital to incorporate geographical and spatial characteristics into the development of prevention and treatment strategies. In addition to Heilongjiang and Inner Mongolia, Sichuan province was found to have a high proportion of DM in MCDs. We further analyze the migrant types of MCDs in the above provinces to find that most of the MCDs in Inner Mongolia and Heilongjiang were due to intra-provincial mobility. This indicates that factors such as prolonged exposure to cold climates, levels of economic development, and dietary practices render the populations in these provinces more prone to chronic diseases. Most of the MCDs in the Zhejiang and Xinjiang provinces were caused by trans-province mobility. As China has transformed into the world's premier manufacturing nation, the Jiangsu-Zhejiang-Shanghai region, with Zhejiang at the forefront, has emerged as a particularly dynamic epicenter of economic development, attracting a significant influx of migrants from across the country. Chronic diseases, as the primary health hazard for migrants, should be given early care and control.

Healthcare-seeking behavior

Local pharmacies were the most selected medical institutions for MCDs after illness, accounting for 28.0%, followed by local public health stations, accounting for 18.9%. Although the notice specifying that expenses incurred by insured individuals for medications listed in the medical insurance directory can be covered by the pooled fund (State Council of the People's Republic of China, 2023) significantly reduces the financial burden for chronic disease patients, there is still considerable room for improvement with respect to the majority of the migrant population and the lack basic medical insurance. It is necessary to increase the number of designated retail pharmacies in cities or communities with a high concentration of migrants and to simplify the reimbursement process considering the migrant population's employment nature. Moreover, establishing medication guides for the migrant population and conducting continuous monitoring are essential to prevent untreated conditions or medication misuse. Based on providing essential health services for migrants, the public health station in the communities should guide them toward appropriate medical treatments and promote a tiered medical system to ensure proper medical care.

Factors influencing no-treatment-ratios

The hotspots found in north-eastern China (Jilin and Liaoning), in the north (Hebei, Beijing, and Tianjin), and in the east (Shandong) also spread to surrounding provinces. Based on the BMHSU, the NHB, HDI, and HE factors had significant effects on the NT-ratio. Among them, the NHB had a positive effect on the NT-ratio, the intensity of which was found to increase from south to north, most significantly in Heilongjiang, Jilin, Liaoning, and Inner Mongolia. Existing research (Song & Zhang, 2022) indicates that satisfaction with local healthcare services in China's north-eastern region lags somewhat behind the national average, which is compounded by the unequal distribution of high-quality resources. Most residents opt for treatment at public hospitals where superior resources are more concentrated, leading to overcrowding at major hospitals (Song & Zhang, 2022). Consequently, the development of a tiered healthcare system, particularly in the north-east, alongside the enhancement of primary healthcare facilities, is vital for ensuring a more equitable distribution of medical resources throughout China. Such measures not only streamline access to appropriate care for the migrant population but also promote the uniformity of basic public health services.

HDI impacts the NT-ratio positively, suggesting that higher *per capita* disposable income for healthcare in each province might paradoxically, and contrary to the conclusions of most previous studies (Tang & Le, 2014; Qu & Zhi, 2015), deter MCDs from seeking treatment. This phenomenon aligns with the new migration economic theory, which posits that migration decisions aim to maximize family welfare, treating migration as a strategy for livelihood. Migrants may halt their mobility once they fulfill their economic objectives, with individuals with higher savings achieving this goal more swiftly (Gu *et al.* 2019). *Per capita* medical disposable income, defined as the remainder of personal income after personal tax deductions, influences labor mobility towards income goals. Therefore, investing in medical funds alone may not suffice to ensure MCDs receive reasonable medical treatment, and it also indicates a complex interplay between economic factors and healthcare-seeking behavior.

HE was found to impact the NT-ratio negatively. Universal health education can effectively reduce the possibility of MCDs choosing no treatment after illness, and the effect is most obvious in the north-east of China. Health education has been included in the primary prevention strategy of HBP and DM in China's health guidelines, and its importance has been increasing in recent years. However, implementation varies from region to region, and its popularity is especially poor in the areas where migrants gather. It requires the local community to focus on the migrants' disease situation and population structure to strengthen the management of health education popularization in various regions, and each region should also "take measures according to local conditions". These should prioritize regions with low health education rates; integrating health education into primary prevention strategies for diseases like hypertension and diabetes is critical.

Limitations

Due to the high mobility and large base of China's migrant population, obtaining continuous tracking data presented challenges. Thus, this study utilized cross-sectional data from the 2017 China Migrants Dynamic Survey. However, it is essential for future research to explore longitudinal data on the migrant population. Furthermore, the factors that influence healthcare-seeking behavior and health outcomes in the MCDs are complex and multifaceted, and the logical relationship (especially the reciprocal action) among the factors in the future needs to be further explored.

Conclusions

Based on the China Migrant Dynamic Survey data in 2017, this study explored the spatial variation and influencing factors of the healthcare-seeking behavior of the MCDs in China by using spatial auto-correlation and GWR. MCDs have a high prevalence and poor initiative to seek medical care; NT-ratios are high; and health services are seriously underutilized. The spatial statistical analysis results showed differences in the geographical distribution of particular medical syndromes of the MCDs, such as HBP, DM, and HBP&DM, which showed a higher prevalence rate in north-east China, Zhejiang, and Xinjiang. NHB, HDI, and HE are the driving factors affecting the NT-ratio. On the one hand, the high mobility and job characteristics of the Chinese inner migrants have severe adverse effects with regard to the prevention and care of chronic diseases. On the other hand, differences in prevalence by place of residence have increased health inequalities. In the future, it is imperative for communities to give a high priority to the health of the MCDs, which focuses on the equitable distribution of quality medical resources. An enhanced infrastructure of primary healthcare facilities and vigorously promoting health education can foster more appropriate medical care for MCDs and significantly improve their health outcomes.

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