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Social Media Big Data-Based Research on the Influencing Factors of Insomnia and Spatiotemporal Evolution

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ABSTRACT Insomnia is a prevalent sleep disorder that causes serious harm to individuals and society. It is closely linked to not only personal factors but also social, economic and other factors. This study explores the influencing factors and spatial differentiation of insomnia from the perspective of social media. This paper chose China's largest social media platform, Sina Weibo, as its data source. Then, based on the collected relevant data of 288 Chinese cities from 2013 to 2017, it explored the impact of economic, social, and environmental factors and an educated population on insomnia. Additionally, the importance and interaction of each influencing factor were analyzed. According to the results, the gross domestic product (GDP), proportion of households connected to the Internet and number of students in regular institutions of higher education are the major factors that influence insomnia, and their influences show obvious spatial nonstationarity. Rapid GDP growth has increased the probability of insomnia, and the positive correlation between the proportion of households connected to the internet and insomnia has strengthened annually. Although the impact of insomnia on college students decreased in some regions, the overall impact was still increasing annually, and spatial nonstationarity was obvious. Properly controlling GDP growth and unnecessary time spent online and guiding people to develop healthy Internet surfing habits and lifestyles will help improve their sleep quality. Our research results will help relevant professionals better understand the distribution of regional insomnia and provide a reference for related departments to formulate regional insomnia prevention and treatment policies.

INDEX TERMS Social media, insomnia, geographically weighted regression model, influencing factors.

I. INTRODUCTION

Insomnia has become a ubiquitous sleep disorder that harms both individuals and society and causes serious social and economic losses [1]. According to a report by the National Sleep Foundation, the prevalence of insomnia in the United States is 33%, with 9% of individuals having regular insomnia and 24% having occasional insomnia [2]. In China, this incidence climbs to 38.2%, which means that nearly 400 million people suffer from insomnia; worse still, this percentage continues to increase every year. Furthermore, more than 60% of the people affected by insomnia were born after 1990 [3], [4]. Insomnia can easily lead to a variety of personal health problems, such as fatigue, endocrine disorders, decreased immunity and other physical and mental illnesses [5], [6]. More seriously, it may trigger a wider range of social problems and economic losses. Individuals who suffer from insomnia are prone to behavioral disorders, which may

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threaten social security. Thus, insomnia is more than simply a personal health issue; it is an important public health problem that affects not only the quality of life but also social security and economic development [7]. On the economic front, the measurable losses alone (including reduced productivity and increased absenteeism, accidents, hospitalizations, and medical expenses due to the rise of morbidity and mortality) that insomnia entails for society amount to hundreds of billions of dollars each year [8], [9].

In recent decades, scholars in the fields of genetics, physiology and psychology have conducted extensive research on insomnia. Their research results provide authoritative theoretical and clinical insights into the cognitive mechanism of insomnia [10]–[13]. In addition, a series of recent tests on the correlation between insomnia and ethnic, social, and economic factors show that some of the factors that can affect insomnia can also influence one another and present reciprocal causation. For example, El-Sheikh *et al*. [14] surveyed 276 third- and fourth-grade children and their family members and found that race has an assignable influence on children's insomnia. Bao *et al*. [15] found through a questionnaire survey of 1,053 volunteers that family income is a risk factor for sleep quality; when the household income is higher, the probability of insomnia is lower. Hsieh *et al*. [16] surveyed 6,445 college students and found that social factors play an important role in adolescents' sleeping problems. However, as mentioned above, most of the existing studies conduct questionnaire surveys among a limited population, and the sample size and questionnaire recovery rate are generally low. In addition, questionnaire surveys inevitably entail problems such as a high aggregation of sampling data and limited test populations, which can bias the reliability of the results and the scalability of the treatment strategy.

With the rapid development of the mobile Internet and the Internet of Things, the world has seen a dramatic increase in the use of social media. Every day, billions of data are generated by hundreds of millions of users on platforms such as Facebook, Twitter and Sina Weibo. Researchers can mine these data to help reveal user behavior patterns and social phenomena without violating ethical constraints. In addition, social media data are exempted from the limitations of sample size, time and space and have the advantage of eliminating nonresponse bias [17]. In recent years, the various attributes of insomnia sufferers with different educational backgrounds and in different age groups have been identified in the vast amounts of information released on social media, such as time, spatial location, and even income, occupation, personality, and hobbies [18]. Previous studies have proven the value of these data in insomnia-related research. For example, Tian *et al*. [19] investigated the topics and insomnia symptoms expressed by randomly sampling, coding and analyzing insomnia-related posts. Scott *et al*. [20] conducted research on the correlation between social media usage habits and insomnia. Given these advantages, this study uses data collected from China's largest social media platform, Sina Weibo, to identify the influencing factors and temporal spatial characteristics of insomnia among Weibo users in different age groups and with different educational backgrounds.

This study is different from previous studies on the relationship between insomnia and related factors, as it focuses on the impact of social, educational, environmental, economic and technological factors and the spatial-temporal features of insomnia. This study has three main implications. First, in the absence of recent clinical or household data provided by medical research institutions, this study explores the influencing factors and the temporal and spatial evolution of insomnia. Second, this study can more objectively verify or refute the predictions of a model because an authoritative data source does exist. Third, the findings of this study can assist in disseminating useful information to people who are susceptible to insomnia and in formulating necessary interventions, thus improving people's livelihood and social welfare. This paper's basic structure is as follows. After the introduction, the research area, procedures, model specifications, and variable collection and processing are presented in Section II. Section III analyzes the experimental results. Section IV provides further analysis of the spatial relationship between three typical explanatory variables and insomnia. Finally, this study concludes with Section V.

II. MATERIALS AND METHODS

A. STUDY AREA

A total of 288 Chinese cities were selected as the research areas (Figure. 1). Most of these cities are located on the southeast side of China's population density line (also known as the Heihe-Tengchong Line), which is home to 96% of China's population and 90% of its gross domestic product (GDP) [21], [22]. Therefore, the results obtained by the research in this part of China have broad applicability. Due to the availability of data, Hong Kong, Macau, Taipei, Tibet, and some new cities or regions were excluded.

B. METHODS AND MODELS

The main procedures of this study include the following: (1) collecting and sorting Weibo data related to insomnia, extracting their position coordinates and calculating the number of insomnia-related posts in each city; (2) selecting and quantifying the potential factors that influence insomnia; (3) evaluating the relative importance of the influencing factors and calculating the interaction among the factors; (4) performing a regression analysis on the influencing factors; and (5) analyzing and interpreting the results. The workflow is shown in Figure 2.

The Lindeman, Merenda, and Gold (LMG) model is used to evaluate the relative importance of each factor, and a geographic detector is applied to calculate the interaction of the influencing factors in step (3). The geographically weighted regression (GWR) model is used for the regression analysis in step (4).

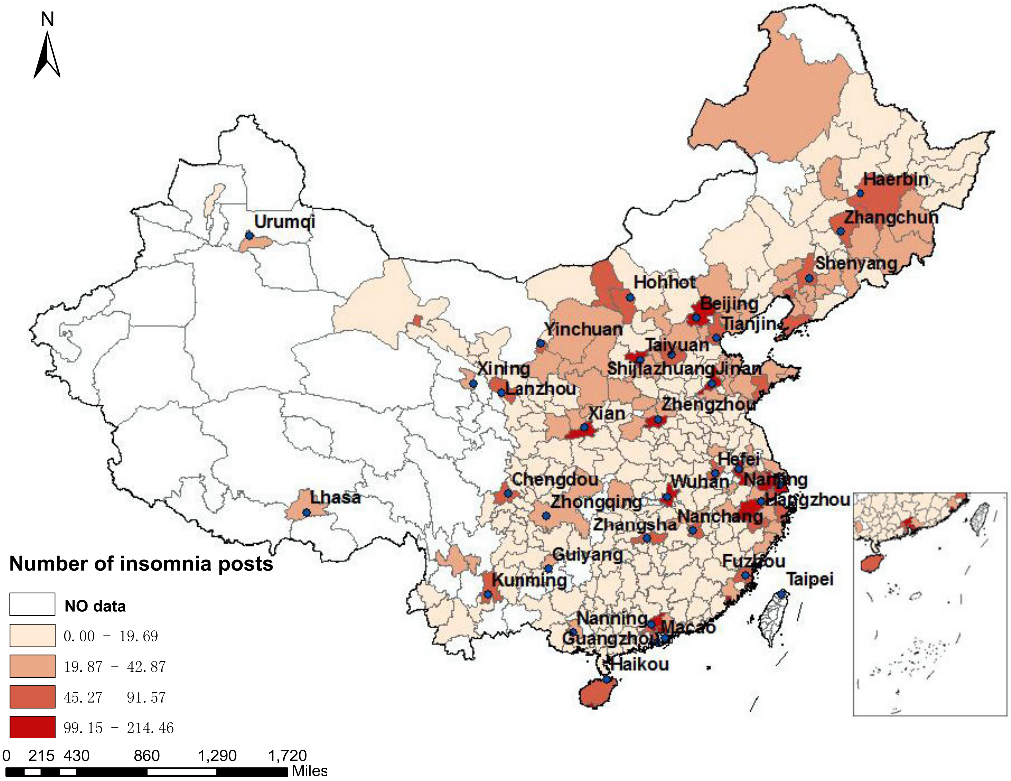

FIGURE 1. The distribution of insomnia posts in Chinese cities.

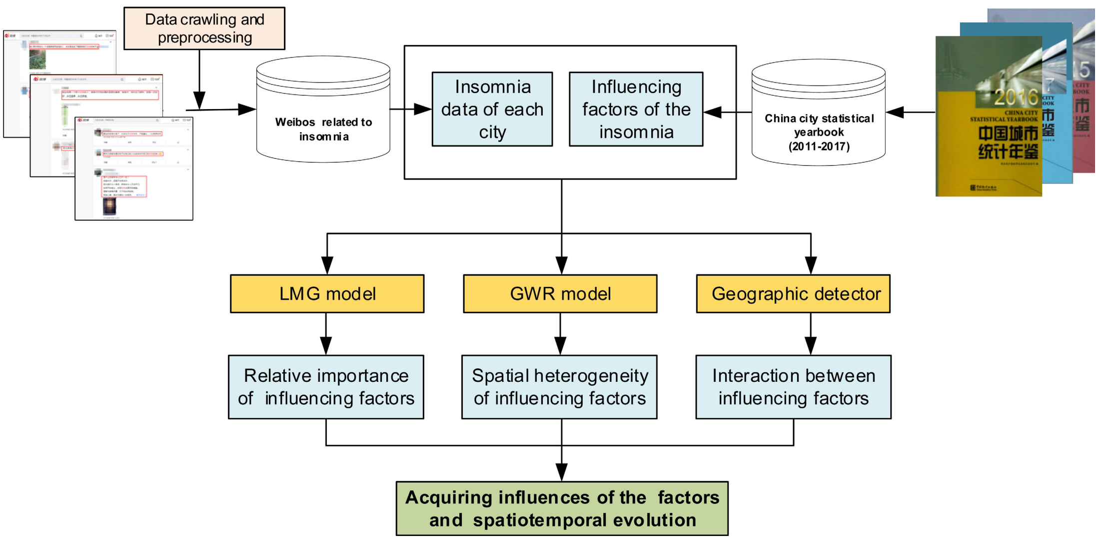

FIGURE 2. Workflow for the detection of influencing factors related to insomnia and its spatiotemporal evolution.

1) GWR MODEL

Scholars commonly employ regression models to discuss the relationship between independent and dependent variables. The general multiple linear regression model is shown in (1):

$$y_i = \beta_0 + \sum_{k=1}^{m} \beta_k x_{ik} + \xi_i \tag{1}$$

Ordinary least squares (OLS) is a common method used to estimate the regression coefficient [23]. The coefficients calculated by OLS are all global, and its regression coefficient does not vary with different spatial locations [24]. However, due to the interaction among spatial objects, heterogeneity exists in the spatial data [25], [26]. Therefore, traditional global regression models such as OLS cannot obtain an effective description of these complex spatial relationships.

To solve this problem, Brunsdon (1996) proposed the GWR model. The GWR model considers the different influences of variables on different regions and reflects the nonstationarity of different spatial parameters [27]. Moreover, this model allows the relationship between variables to change with the spatial location and can provide results that are more realistic by using spatial visualization to perform a spatial comparative analysis on different geographic areas [28]. The definition of the GWR model is shown in (2):

$$y_i = \beta_{i0}(u_i, v_i) + \sum_{k=1}^{m} \beta_{ik}(u_i, v_i)x_{ik} + \xi_i \quad i \in [1, n] \tag{2}$$

where y_i is the value of sample i, (u_i, v_i) is the spatial coordinate of sample i, and m is the number of influencing factors. x_{ik} is the kth influencing factor of sample i, and ξ_i is the residual. Additionally, $\beta_{i0}(u_i, v_i)$ is the spatial intercept of sample i, $\beta_{ik}(u_i, v_i)$ is the regression coefficient of the influencing factors k of sample i, and the calculation formula is shown in (3):

$$\beta(u_i, v_i) = (X^T W(u_i, v_i)X)^{-1}X^T W(u_i, v_i)y \tag{3}$$

where X represents the independent variable matrix, and $W(u_i, v_i)$ is a diagonal matrix with diagonal elements of w_{ij}. This study selects the Gaussian function as the weight function, and its mathematical expression is shown in (4):

$$w_{ij} = \exp[-\frac{1}{2}(\frac{d_{ij}}{b})^2] \tag{4}$$

where b is bandwidth, described as a fixed distance or a fixed range of nearest neighbors. The choice of bandwidth has a significant impact on the GWR results, and AIC is often used to identify a suitable bandwidth. When AIC reaches its minimum, the GWR model obtains the optimal bandwidth. When the number of samples is not sufficiently large, AIC should be converted to AICc to improve accuracy [26].

2) LMG MODEL

The LMG method is also called the average semi-bias correlation coefficient flat method and is often used to quantify the importance of each of the affecting factors in the model for regression analysis [29]. The algorithm was proposed by and named after Lindeman, Merenda, and Gold in 1980. The independent contribution of each regression variable and its interaction with the remaining variables in the regression are fully considered without the need for normalization and nonnegative correction. The LMG model considers a given independent variable n and its permutation. The relative importance of the independent function can be expressed as (5):

$$\text{LMG}(x_i) = \frac{1}{n!} \sum_{r_{permutation}} R^2(x_i|r)) \tag{5}$$

where $r_{permutation} = (r_1, r_2, \ldots, r_n)$ is the order in which the independent variable enters the equation and is a permutation of the subscripts {1, 2...,n} of the independent variable, and $R^2(x_i|r)$ is the continuous sum of the squares of x_i in the rth order.

3) GEOGRAPHIC DETECTOR

Geographic detectors are indexes based on the "power of determinant" metrics and are combined with GIS technology and set theory to effectively identify the interactions among multiple factors. In geospatial terms, almost every phenomenon has its own affecting factors, and some phenomena are the result of the interaction of multiple factors. For geographic detectors, the detected elements can be tested as long as they are related [30]. There are four types of detectors, namely, differentiation and factor detectors, risk zone detectors, ecological detectors, and interaction detectors. At present, geographic detectors are widely used in medical science, disaster assessment, land use, and social economics. The mathematical expression of the geographic detector is shown in (6):

$$Q_{D,H} = 1 - \frac{1}{n\sigma^2}\sum_{i=1}^{n} n_i\sigma_i^2 \tag{6}$$

where $Q_{D,H}$ is the explanatory power of affecting factor D, H is the number of classifications of factor D, n is the sample size, σ^2 is the variance in the number of insomnia posts in the study area, n_i denotes the sample number of the i th parcel, and σ_i^2 is the variance in the number of insomnia posts in the i th parcel, where the value of $Q_{D,H}$ is between 0 and 1.

For the purposes of this study, insomnia is a complex psychological and physiological process and may involve the interaction of multiple factors. The interaction detector, one of the geographic detectors, is used to identify whether two affecting factors have an interactive effect on insomnia, as described in Table 1.

C. DATA COLLECTION AND PREPROCESSING

1) DEPENDENT VARIABLE

The dependent variable in this study was the location coordinates of insomnia-related Weibo posts in 288 Chinese cities in 2013, 2014, 2015, 2016 and 2017. The data acquisition method and process are as follows.

First, a custom data crawler based on the Scrapy framework was established to crawl Weibo data by using the keywords "睡不着(sleepless)" and "失眠 (insomnia)" in posts from 2013, 2014, 2015, 2016, and 2017. Specifically, in each Weibo post, the crawled fields include information such as the Weibo content, publishing time, and location coordinates. A total of 2,912,081 data points was crawled.

Second, because not all posts that contain the keywords are related to insomnia and this study focuses on the spatial location of insomniacs, we filter out the posts without location information. Moreover, a binary text classifier based on a supervised classification is established to identify insomnia posts. Supervisory classification requires the manual labeling of training data, but there are currently no open data available. In this study, 5,000 posts were randomly selected and

TABLE 1. Descriptions and interaction relationships.

Legends	Descriptions	Interactions
	$Q(x_1 \cap x_2) < \min[Q(x_1), Q(x_2)]$	Nonlinear attenuation
	$\min[Q(x_1), Q(x_2)] < Q(x_1 \cap x_2) < \max[Q(x_1), Q(x_2)]$	Nonlinear attenuation (single factor)
	$Q(x_1 \cap x_2) > \max[Q(x_1), Q(x_2)]$	Enhancement (two factors)
	$Q(x_1 \cap x_2) = Q(x_1) + Q(x_2)$	Independent
	$Q(x_1 \cap x_2) > Q(x_1) + Q(x_2)$	Nonlinear enhancement

TABLE 2. The system of influencing factors.

Dimension	Influencing Factors	Abbreviation	Unit
Economy and technology	Regional GDP	GDP	Ten thousand
	Proportion of households connected to the Internet	PHCI	%
Society	Population density	PD	Person/km2
	Unemployment rate	UR	%
Education	Number of students in regular institutions of higher education	NS_RIHE	Person
	Number of students in regular secondary schools	NS_RSS	Person
Environment	Volume of sulfur dioxide emissions	V_SDE	Ton
	Volume of industrial soot (dust) emissions	V_ISE	Ton
	Greening rate	GR	%

independently labeled by three researchers with mental health experience. When no consensus was reached regarding the label, the majority decision principle was adopted. According to previous studies, the support vector machine (SVM) has high accuracy in Weibo text classification [3], [19]. Thus, the SVM was employed to distinguish the target Weibo texts. The Weibo texts are vectorized as the input of the SVM, and they are classified into the two categories of the targeted and the off-targeted. In this study, the accuracy of the SVM classification is 82.3%.

Ultimately, there are 62,397 Weibo data points with nonempty location coordinates (5,259 in 2013, 8,352 in 2014, 14,208 in 2015, 15,217 in 2016, and 19,361 in 2017). The coordinate information is extracted, overlay analysis and statistical analysis are conducted with the vector map of Chinese urban administrative regions, and the number of insomnia posts in 288 cities is obtained. Considering the uneven distribution of the population in the study area, the results may be biased; therefore, it is necessary to make a population correction. According to previous studies, this paper takes the ratio of the number of Weibo texts related to insomnia in each prefecture-level city to the population of the region as the dependent variable [31].

2) INFLUENCING FACTORS

Considering the accessibility of the data and combining the related studies in China and internationally, this study extracts data from the China Urban Statistical Yearbook (2013,2014, 2015, 2016, 2017) and selects nine influencing factors from the four dimensions of society, education, environment, economy and technology as variables. The system of these variables is shown in Table 2.

GDP is the market value in monetary terms of the total final products and services in a country or region during a period of time (a year, season or month). GDP can reveal the vitality and influence of regional economic development and is used universally to measure the regional economic development level [32]. The proportion of households connected to the Internet (PHCI) is generally considered to be an important indicator of the development of science and technology [33]. In the Internet era, the channels through which people browse and disseminate information have been greatly expanded, and the Internet has profoundly affected the way that people live and produce [34], [35]. Population density (PD) is the population per unit area, which is frequently denoted as the population per square kilometer, and reflects the difference in the regional population [33]. The unemployment rate (UR), which is the ratio of the unemployed population to the working population, is used to evaluate idle labor production and is the primary factor used to reveal the unemployment status in a certain country or region [33]. PD and UR have a remarkable correlation with the occurrence and spread of many diseases [36], [37].

Sleep quality is closely related to students' intelligence and physical growth, as insomnia can irreparably undermine the health of students. The influence of insomnia varies across age groups [38]–[40]. Based on the classification in the China Urban Statistical Yearbook, we selected the number of regular

TABLE 3. Regression results using OLS.

Parameter	2013 Coefficient	2013 t-ratio	2013 Robust-Pr	2013 VIF	2014 Coefficient	2014 t-ratio	2014 Robust-Pr	2014 VIF	2015 Coefficient	2015 t-ratio	2015 Robust-Pr	2015 VIF
GDP	0.0011	10.2840	0.0000***	3.7447	0.0017	9.9200	0.0000***	4.1616	0.0012	6.4790	0.0000***	3.3610
PD	0.0010	1.7180	0.0870	1.6248	0.0019	1.9660	0.0503	1.6490	0.0019	1.4320	0.1530	1.6782
UR	-0.1154	-1.0540	0.2927	1.0953	-0.1349	-0.7480	0.4549	1.0995	-0.2305	-1.1570	0.2480	1.0826
NS_RIHE	0.0799	5.8250	0.0000***	2.1394	0.1838	8.0330	0.0000***	2.2188	0.2518	8.6840	0.0000***	2.0968
NS_RSS	0.0542	-4.1050	0.0001***	1.8947	0.1105	-4.8980	0.0000***	2.0107	-0.1586	-5.2620	0.0000***	1.9279
V_SDE	-0.0113	-3.7930	0.0002***	1.2975	-0.0310	-4.0540	0.0001	2.2298	-0.0050	-0.5120	0.6090	1.4598
V_ISE	-0.0001	-0.1020	0.9189	1.0365	0.0013	0.2000	0.8413	1.7507	0.0011	0.4230	0.6720	1.0483
PHCI	0.1046	8.2180	0.0000***	1.6788	0.0695	3.7350	0.0002***	1.7277	0.2092	9.2990	0.0000***	1.5800
GR	0.0093	1.7270	0.0852	1.4450	-0.0286	-3.4370	0.0007***	1.4350	0.0242	0.4800	0.6320	1.0826

Parameter	2016 Coefficient	2016 t-ratio	2016 Robust-Pr	2016 VIF	2017 Coefficient	2017 t-ratio	2017 Robust-Pr	2017 VIF
GDP	0.0016	5.2780	0.0000***	3.0883	0.0012	3.2570	0.0013**	2.5866
PD	-0.0674	-0.1730	0.8630	1.5671	-0.1848	-0.4050	0.6861	1.6527
UR	0.0001	0.0470	0.9620	1.1203	-0.0003	-0.1020	0.9191	1.1935
NS_RIHE	0.4045	7.6340	0.0000***	2.0931	0.2062	2.6340	0.0089**	2.2749
NS_RSS	-0.2700	-4.8390	0.0000***	1.9459	0.1644	-2.1860	0.02968*	1.9674
V_SDE	-0.0062	-0.2020	0.8400	1.7512	0.0791	1.4550	0.1467	1.9027
V_ISE	0.0019	0.0850	0.9320	1.5298	-0.0073	-0.1440	0.8853	1.7319
PHCI	0.4527	9.7360	0.0000***	1.6349	0.4391	6.9210	0.0000***	1.5665
GR	0.0806	0.7760	0.4390	1.1106	-0.0089	-0.0520	0.9588	1.1165

Note: * represents a statistically significant probability. "***": p<0.0001, "* *": p<0.001,"*": p<0.01

secondary schools (NS_RSS) and the number of regular institutions of higher education (NS_RIHE) to analyze the spatial differentiation between school-age children at different education levels and insomnia.

The volume of sulfur dioxide emissions (V_SDE) refers to the amount of sulfur dioxide that an industrial enterprise discharges into the atmosphere during fuel combustion and production processes [33]. The volume of industrial soot (dust) emissions (V_ISE) refers to the total mass of smoke and industrial dust discharged into the atmosphere by enterprises during fuel combustion and production processes [33]. According to previous research, excessive emissions of sulfur dioxide and industrial dust in the air can cause dizziness, chest tightness, and shortness of breath and severely affect sleep [41], [42]. The urban greening rate (GR) refers to the ratio of the area of green space in the urban built-up area to the total built-up area. Generally, the GR affects the cleanliness of the air and the oxygen content of the air, which affects people's sleep [43], [44].

III. RESULTS

A regression analysis was performed based on the OLS model for the influencing factors of insomnia. The coefficients of each influencing factor and their significance are shown in Table 3. The statistical result of Koenker is statistically significant; therefore, we employ Robust-Pr to estimate the statistical significance of the influencing factors. Furthermore, the multicollinearity between the variables was judged by the VIF and PCC methods. Generally, there is no multicollinearity and no redundant variable if the VIF is less than 7.5, and the PCC is less than 0.9 [45], [46]. In Table 3, the VIF values of all variables from 2013 to 2017 are less than 7.5, and the PCC values (Figure 3) are less than 0.9, which indicates that there is no multicollinearity among the influencing factors.

Koenker (BP) is mainly used to test whether the explanatory variables and dependent variables in the model have a consistent relationship both in the location space and data space. If the test result shows statistical significance, we can say that each explanatory factor in the model is statistically nonstationary and suitable for GWR analysis [26], [47]. During our study period, p remained below 0.001, which proves its significant nonstationarity and suggests that the GWR model is well applicable for our analysis. Our final estimated result of GWR is a matrix of coefficients whose minimum, median, and maximum values are shown in Table 5.

Table 4 compares the GWR and OLS results. Normally, when the AIC is lower, the fit of the variables to the model

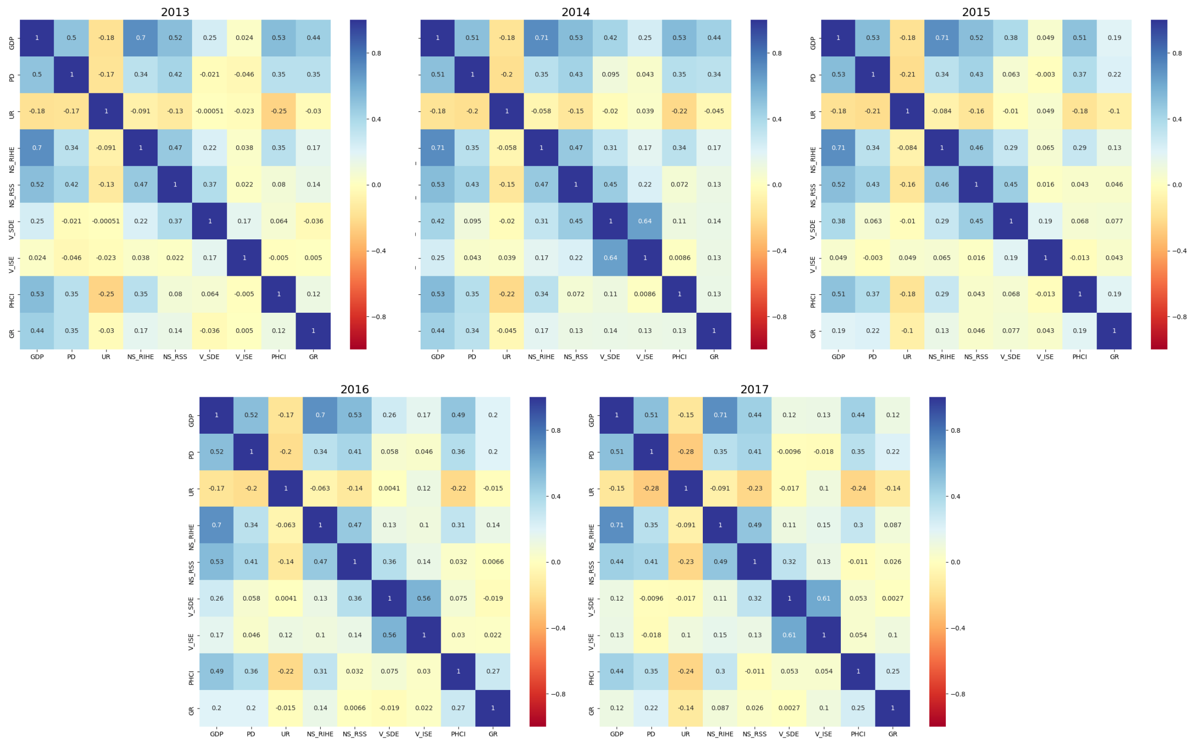

FIGURE 3. Global correlation coefficient matrix.

TABLE 4. Comparison of the OLS and GWR results.

	Year									
	2013		2014		2015		2016		2017	
	OLS	GWR	OLS	GWR	OLS	GWR	OLS	GWR	OLS	GWR
AICc	1372.184	1053.331	1663.535	1217.394	1839.573	1115.438	2193.693	1730.714	2378.677	1891.597
R2	0.795	0.922	0.745	0.903	0.742	0.885	0.691	0.816	0.417	0.792
Adjusted R2	0.788	0.919	0.737	0.900	0.734	0.881	0.681	0.810	0.398	0.782
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.881	0.000	0.000

is better. In addition, a higher adjusted R2 usually results in the model being able to explain more dependent variables. As we can see in Table 4, GWR obtains a lower AICc and a higher adjusted R2 compared with OLS, which indicates that GWR is a better option for explaining the dependent variables and predicting the relationships among the variables.

A. GWR MODEL

Table 5 shows that the R^2 values of the GWR are 0.9220, 0.9031, 0.8847, 0.8162 and 0.7920 (adjusted R^2 values are 0.9194, 0.9000, 0.8810, 0.8102 and 0.7831) for the five years studied, respectively, which suggests that the model fits the data well. The minimum of the regression coefficients of GDP, PD, UR, NS_RIHE, V_SDE, V_ISE, PHCI and GR is negative, and the maximum is positive, which indicates that these factors are heterogeneous in direction. Notably, the maximum and minimum of the NS_RSS for all five years are positive, which indicates that NS_RSS presents the strongest positive spatial correlation with insomnia. For NS_RSS, the positive correlation with insomnia in most areas can be presented by the positive median of the regression coefficients.

B. THE IMPORTANCE OF THE INFLUENCING FACTORS

Figure 4 presents the results of the LMG model. In the five years studied, the relative importance of GDP in percentages is 32.08%, 32.82%, 26.99%, 24.18% and 23.38%, respectively, which shows a slight annual trend. Conversely, the influence of PHCI on insomnia increases over time and increases from 25.99% in 2013 to 46.29% in 2017. Notably, although the importance of NS_RIHE increased slightly from 2013 to 2014, it declined annually, from 32.00% in 2015 to 17.52% in 2017.

TABLE 5. **The estimation results of the GWR model.**

Parameter	Year														
	2013			2014			2015			2016			2017		
	Minimum	Median	Maximum	Minimum	Median	Maximum	Minimum	Median	Maximum	Minimum	Median	Maximum	Minimum	Median	Maximum
GDP	-0.4927	-0.0415	0.6698	-0.4535	0.0461	0.4784	-0.4546	0.1886	0.8120	-0.2160	0.4679	1.5429	-0.0417	0.5416	1.0854
PD	-0.7017	-0.0231	0.4313	0.0003	0.0014	0.0032	-0.0008	0.0011	0.0022	-0.0007	0.0010	0.0020	-0.0010	0.0007	0.0023
UR	-0.0003	0.0009	0.0020	-0.0034	0.0012	0.0035	-0.0063	0.0013	0.0047	-0.0066	0.0006	0.0054	-0.0078	0.0007	0.0092
NS_RIHE	-0.0012	0.0011	0.0044	-1.1822	-0.2278	0.2719	-0.7829	-0.0595	0.3608	-2.7121	-0.2240	0.7174	-3.5664	-0.6839	0.1422
NS_RSS	0.0058	0.0950	0.1771	0.0164	0.2460	0.3345	0.0019	0.3421	0.4913	0.0818	0.4892	0.7445	0.1804	0.3355	0.8357
V_SDE	-0.1591	-0.0478	-0.0033	-0.3351	-0.0963	-0.0153	-0.3751	-0.1278	0.0014	-0.3706	-0.1641	0.0079	-0.2724	-0.1289	0.0296
V_ISE	-0.0475	-0.0045	0.0220	-0.0891	-0.0211	-0.0006	-0.0590	-0.0070	0.0351	-0.0677	-0.0082	0.0847	-0.0760	0.0981	1.3544
PHCI	-0.0489	-0.0010	0.0021	-0.0387	0.0009	0.0332	-0.0048	0.0002	0.0079	-0.1191	-0.0127	0.0425	-0.9690	-0.0443	0.2057
GR	-0.0036	0.0683	0.2164	-0.3065	0.0428	0.2028	-0.1718	0.1116	0.3702	0.0817	0.4717	0.7276	0.0640	0.3434	0.5944
R^2	0.9220			0.9031			0.8847			0.8162			0.7920		
Adjusted R^2	0.9194			0.9000			0.8810			0.8102			0.7831		

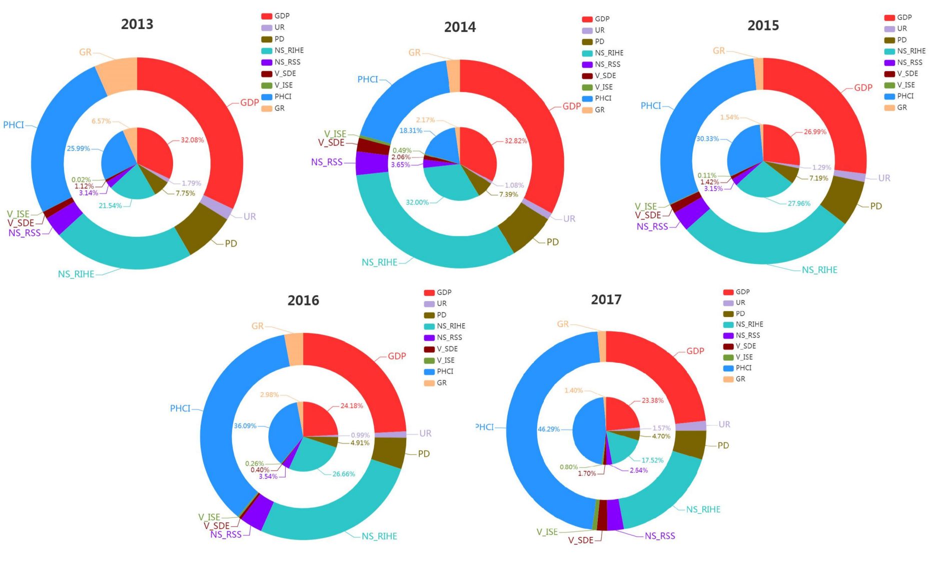

FIGURE 4. **Relative importance of influencing factors.**

TABLE 6. The results of the interaction relationship.

Description	Year 2013 Result	2014 Result	2015 Result	2016 Result	2017 Result
GDP∩UR	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear
GDP∩PD	Enhanced, bi-	Enhance, nonlinear	Enhanced, bi-	Enhanced, bi-	Enhance, nonlinear
GDP∩NS_RIHE	Enhanced, bi-	Enhanced, bi-	Enhanced, bi-	Enhanced, bi-	Enhanced, bi-
GDP∩NS_RSS	Enhanced, bi-	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear
GDP∩V_SDE	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear
GDP∩V_ISE	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear
GDP∩PHCI	Enhanced, bi-	Enhanced, bi-	Enhanced, bi-	Enhanced, bi-	Enhanced, bi-
NS_RIHE∩UR	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear
NS_RIHE∩PD	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear
PHCI∩RSS	Enhanced, bi-	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear
PHCI∩UR	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear
PHCI∩PD	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear	Enhance, nonlinear

Note: Enhance, nonlinear; Enhanced, bi-

C. THE INTERACTION OF THE INFLUENCING FACTORS

Based on the results of the LMG model, this paper analyzes the interaction among the three most important impact factors (GDP, NS_RIHE, and PHCI) and other factors, as shown in Table 6. Over the 5-year study period, the interactions between GDP & PD, GDP & NS_RIHE, and GDP & NS_RSS all aggravated insomnia. Meanwhile, the interactions between GDP & UR, GDP & V_SDE, GDP & V_ISE, NS_RIHE & UR, and NS_RIHE & PD resulted in a significant nonlinear enhancement to insomnia. Except for a two-factor enhancement relationship with RSS in 2013, the interactions of PHCI with the other factors all showed nonlinear enhancement. According to the above findings, compared with the effect of a single factor, the interactions among GDP, NS_RIHE, PHCI and the other factors lead to a greater impact on insomnia.

IV. DISCUSSION AND POLICY

A. GDP

During the five-year study period, the minimum values of the GWR regression coefficient (Table 5) of GDP are negative, while the maximum values remain positive, which indicates that GDP and insomnia are significantly spatially nonstationary.

It can be observed in Figure 5 that the regression coefficient of GDP shows obvious spatial heterogeneity and regularity over time. Specifically, in 2013, the impact of GDP on insomnia gradually shifted from a positive correlation to a negative correlation from north to south. The regions with the strongest positive correlation are mainly concentrated in Northeast China and parts of North China, while in the southeast coastal areas, insomnia is found to be negatively correlated with GDP. From 2014 to 2016, the impact of GDP on insomnia in Northeast China gradually changed from positive to negative. In contrast, the impact in the southern region has changed in the opposite direction. It is worth noting that the GDP growth rate of Northeast China in 2013 was still higher than the GDP growth rate of the entire country. However, in 2015, it shifted into a significant downward trend, and by 2016, the share of Northeast China's GDP to national GDP declined for five consecutive years [48]. In 2017, as Liaoning and Heilongjiang's GDP growth rates increased, Northeast China showed signs of economic recovery, especially in Liaoning, where the GDP growth rate turned from negative to positive [48]. However, in Southern China, especially in the southeastern coastal areas, GDP growth has accelerated with the rapid development of China's economy. As a result, work and living stress has surged in these regions, which increases the likelihood of insomnia.

Accordingly, the government and relevant departments need to properly control the growth rate of GDP and transform GDP growth. On the one hand, the rapid growth of GDP has increased the possibility that the wealth gap will widen in a short period of time. Studies have shown that the gap between the rich and poor is significantly negatively related to insomnia; that is, in cities with high wealth inequality, when the household income is lower, the quality of people's sleep is worse and the probability of insomnia is greater [14], [15]. On the other hand, in many parts of China, GDP growth comes at the expense of the environment. Previous studies have indicated that improving environmental quality is an effective way to enhance sleep health and reduce health disparities [49], [50]. If people live in polluted air for a long time, it will cause a series of problems, such as insufficient blood supply to the brain, which triggers insomnia [44], [51]. Therefore, appropriate control of the growth rate

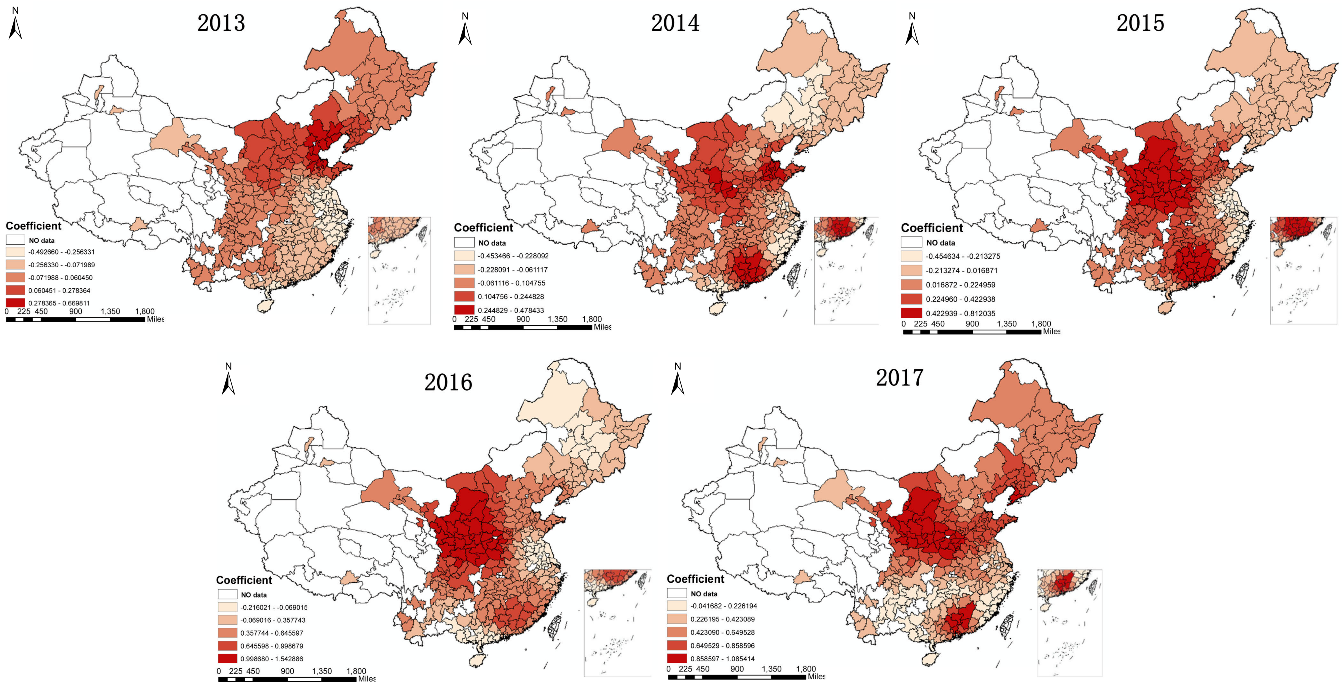

FIGURE 5. The spatial coefficient distribution for GDP from 2013 to 2017 based on the GWR model.

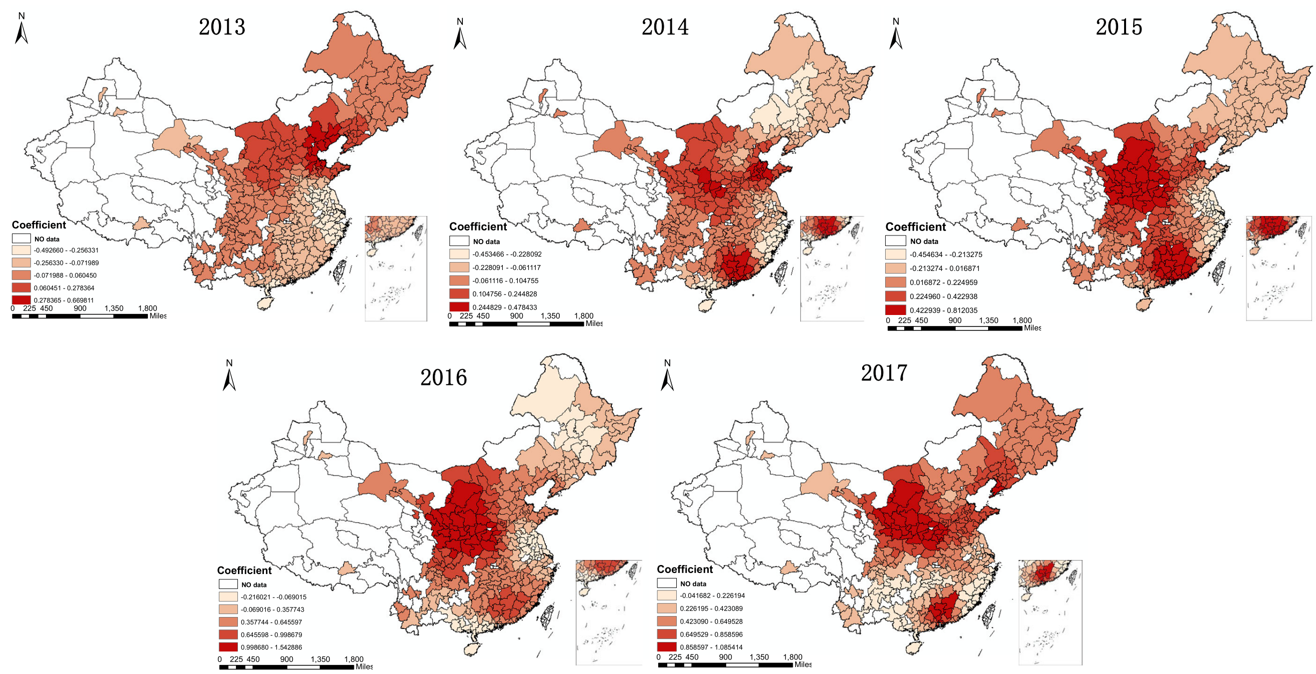

FIGURE 6. The spatial coefficient distribution for PHCI from 2013 to 2017 based on the GWR model.

of GDP could be beneficial to ease insomnia and improve sleep.

B. PHCI

Figure 6 demonstrates the spatial differentiation of the impact of the Internet access rate on insomnia. It can be observed from the figure that during the five years of the study, both positive and negative correlations existed between the Internet access rate and insomnia. In 2013, a negative correlation was predominant nationwide; in 2014-2016, the area with a positive correlation expanded slightly. In 2017, the figure shows that the Internet access rate and insomnia in most parts of the country were positively related.

Behind this phenomenon is an increase in the number of Internet users in China. As of 2018, there were approximately 700 million Internet users in China, and nearly 600 million of

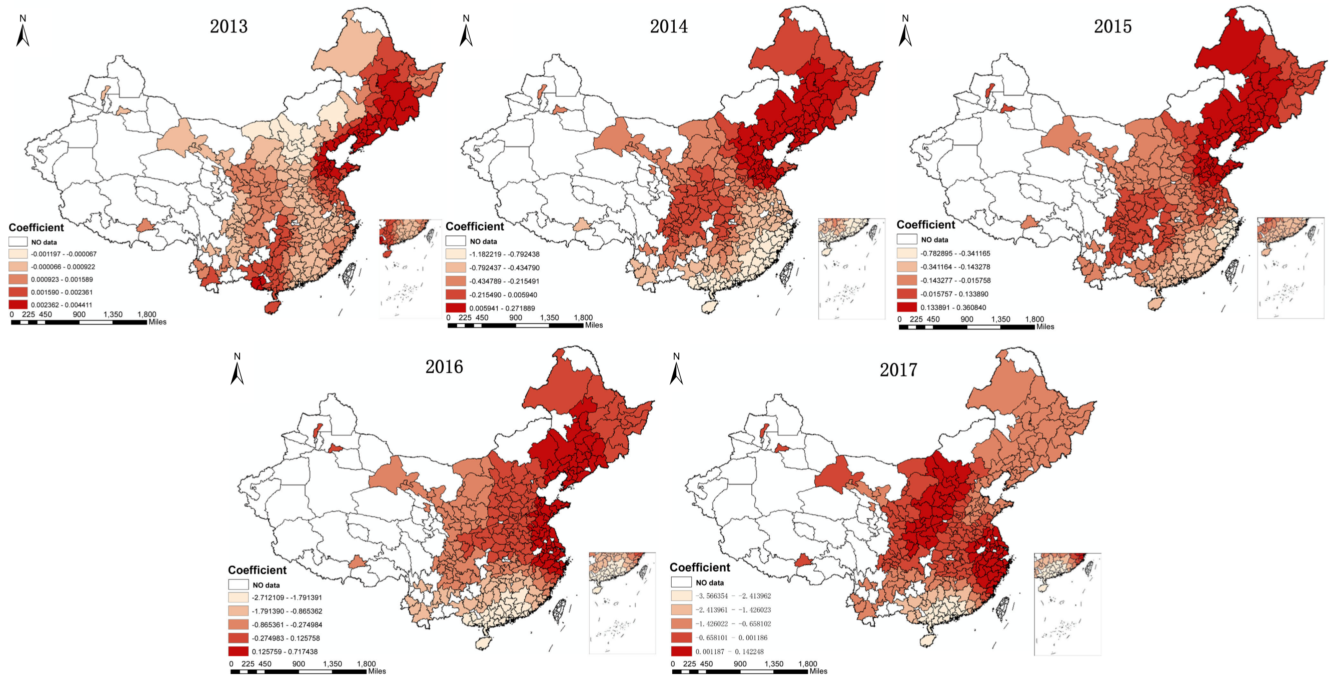

FIGURE 7. The spatial coefficient distribution for NS_RIHE from 2013 to 2017 based on the GWR model.

these users accessed the Internet from mobile phones [52]. It has become a part of many people's lifestyle to watch videos and livestreams through mobile phones or computers. Previous studies have shown that moderate daily Internet use is beneficial to people's physical and mental health and to sleep quality. However, the incidence of insomnia is nearly 50% higher in people who are online for more than 6 hours per day, and people who go online for more than an hour before going to bed excite their brains through the ingestion of a large amount of information [53], [54]. Moreover, radiation from mobile phones, computers or other Internet devices interfere with the brain, which leads to delays in falling asleep, causes adverse reactions such as headaches and dizziness, and seriously affects sleep quality [55].

Therefore, for individuals, it is important to appropriately reduce unnecessary time spent online and to develop a healthy lifestyle; for relevant government sectors, effective intervention measures should be formulated, such as education, programs that promote sleep health, and the timely organization of mass sports activities, so that people can develop healthy online and offline lifestyles, and for mobile phone app and computer software manufacturers, health reminders and health warning modules should be added to help users regulate their emotions and improve sleep quality [56].

C. NS_RIHE

Table 5 reveals that the median regression coefficient of the number of college students in the study period remains negative for most of the time, which indicates that it has a negative correlation with the number of posts about insomnia in most areas. Figure 7 reflects the spatial differentiation of the number of college students and insomnia. It is clear from the figure that the impact of insomnia on college students in the five-year study period has spatial instability. In 2013, the number of college students in most parts of the country was positively related to insomnia. The region with the strongest positive correlation was mainly distributed in Northeast China, North China, and the southeast coastal areas. From 2014 to 2016, in some southern coastal areas, the correlation between insomnia and the number of college students gradually changed from positive to negative, while the area north of the Yangtze River maintained a strong positive correlation. In 2017, the positive correlation was mainly found in some provinces in North China and in the Yangtze River Delta, but in most parts of the country, insomnia was negatively correlated with the number of college students. One of the main reasons for this phenomenon is that college students as a group are about to step into society and face pressure from both academics and employment [4], [57], [58]. During the time period covered by this study (2013-2017), the Chinese government implemented a series of preferential and stimulus policies, such as student loans for college students and public entrepreneurship and innovation subsidies, to ensure that college students could successfully complete their studies and secure employment. Given the support of these policies, the financial concerns of college students from families with difficult financial conditions were reduced; they were enabled to start their own businesses while still in college, which thus promoted an atmosphere of entrepreneurship. In this context, China has fostered the emergence of a large quantity of start-up companies, which has greatly eased the employment pressure on college students. To a certain extent, this has contributed to alleviating insomnia among college students.

Nevertheless, as shown in Figure 7, the maximum regression coefficients in 2014, 2015, and 2016 were 0.27, 0.36, and 0.72, respectively. These figures indicate that the problem of insomnia among college students is still serious, which is consistent with the results from previous research [39], [59]. Although the regression coefficient dropped to 0.14 in 2017, insomnia among college students still needs attention. If not taken seriously, it could cause mental disorders such as anxiety and depression. Therefore, the relevant sectors should take measures and formulate corresponding policies and regulations to promote the physical and mental health of college students. In addition, schools should improve the campus environment. At the same time, it is necessary to further strengthen mental health education for college students, allow mental health to infiltrate education, and establish correct mental health concepts. Finally, students should reasonably regulate their emotions and attempt to maintain a good sleep quality, which can help prevent depression, anxiety, anger, fear and other adverse psychological conditions [60], [61].

V. CONCLUSION

This study chooses China's largest social media platform, Sina Weibo, as a data source for data from 288 Chinese cities in 2013, 2014, 2015, 2016 and 2017. Based on the data, we investigate the effects of economic, technological, social, educational and environmental factors on insomnia and reveal their spatial correlation by using the GWR model, LMG model and geographic detectors. The main conclusions are as follows.

According to the GWR results, the influences on insomnia of factors such as GDP, PD, PHCI, UR, NS_RIHE, NS_RSS, V_SDE, V_ISE, PHCI and GR show a certain degree of heterogeneity and spatial differentiation. The LMG assessment reveals that GDP, the proportion of households connected to the Internet, and the number of college students are three important factors that reflect economic, technology and education levels, respectively. In addition, the results of the geographic detection show that the interaction of the three main factors and other factors has larger impacts on insomnia than single factors. Proper control of the GDP growth rate can be beneficial to the improvement of insomnia. There is a positive correlation between the proportion of Internet access among families and insomnia in most areas. People should appropriately control unnecessary online time, and the government should formulate corresponding intervention measures. Relevant software manufacturers should appropriately increase health reminders and early warning health modules to guide users to develop healthy Internet habits and lifestyles. During the study period, we observed obvious spatial heterogeneity in the relationship between the number of college students and insomnia. Because of the Chinese government's preferential policies for college students, this relationship in most parts of China has gradually changed from a positive correlation to a negative correlation. However, generally, the prevalence of insomnia among college students is increasing. In this regard, more attention and active measures are required to improve the physical and mental health of college students.

The findings above can provide a reference for helping not only researchers to better understand the regional distribution pattern of insomnia but also local governments to formulate insomnia prevention and treatment policies in accordance with local characteristics, which is of practical significance. Nevertheless, this study has limitations. First, the insomnia data of this study comprise location information posted by users, which leads to a certain degree of data sparsity. Therefore, our results may entail inaccuracies in the spatial correlation between insomnia and the selected influencing factors. Second, the potential influencing factors of insomnia were not chosen with sufficient rigor, and further research and consideration of other methods are needed to select more factors. In the future, we will use spatial statistics or data mining methods to determine the scope and extent of the influence of different types of factors. Then, the optimal model and method will be applied to describe the temporal and spatial changes in insomnia and its influencing factors.

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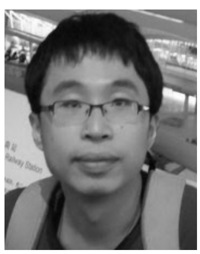

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