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Spatiotemporal analysis of health poverty in China amid social change: regional inequalities, socioeconomic drivers, and policy implications

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This study develops a Health Poverty Index (HPI) that integrates health rights, capabilities, and risks to analyze provincial disparities in China from 2010 to 2020. Utilizing data from the China Family Panel Studies (CFPS) encompassing 76,999 households, we measured the incidence, depth, and spatiotemporal drivers of health poverty through Geographically and Temporally Weighted Regression (GTWR). The results indicate a national decline in HPI from 0.338 to 0.163, with incidence rates falling from 68.5% to 37.9%. However, the reduction in poverty depth was marginal (from 0.494 to 0.429, a marginal reduction of 0.065). Western provinces, such as Guizhou (HPI = 0.503 in 2010), exhibited higher initial HPI but experienced more rapid improvements ("high baseline, rapid decline"), whereas eastern regions like Shanghai saw substantial reductions in incidence but persistent depth, indicative of "asynchronous breadth-depth alleviation." GTWR analysis identified key drivers: economic growth (measured by per capita GDP) most effectively reduced HPI in southwestern China during 2014–2016, but its impact diminished after 2020 in the northeast due to industrial constraints. Population aging exacerbated HPI in the southwest, while low education heightened risks nationwide, particularly in technology-intensive eastern provinces. Enhanced healthcare resource allocation (e.g., nurse density) significantly mitigated HPI, though efficiency gaps remained in the west. Additionally, reductions in pollution aligned with improved governance after 2016. These findings highlight the necessity for region-specific policies: expanding the healthcare workforce in the west, implementing equity-oriented interventions in the east, and adopting aging-adapted reforms in the northeast to achieve sustainable eradication of health poverty.

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Introduction

In 2015, the United Nations Sustainable Development Summit adopted the "Transforming Our World: The 2030 Agenda for Sustainable Development," which outlines 17 Sustainable Development Goals (SDGs). The agenda's first goal aims to eradicate all forms of poverty globally, while the third goal focuses on ensuring healthy lives and promoting the well-being for individuals of all ages. Health and poverty remain central challenges to global sustainable development. As the largest developing country, China has historically grappled with poverty as a significant barrier to social progress. According to World Bank standards, China accounted for up to 75% of the global poor population between 1981 and 2018 (World Bank, 2025). In 2013, China implemented a targeted poverty alleviation policy, achieving the historic milestone of eliminating absolute poverty by 2020, marking a monumental contribution to global poverty reduction (Wan et al., 2021). However, relative and multidimensional poverty have since emerged as critical concerns (Alkire and Fang, 2019). The 2024 Global Multidimensional Poverty Index (MPI) report by the United Nations Development Program (UNDP) reveals that health-related deprivation now contributes 35.2% to multidimensional poverty in China, surpassing the living standards dimension at 25.6% (UNDP, 2024). This underscores health poverty as a significant bottleneck hindering further progress in China's poverty alleviation efforts.

Health poverty is fundamentally rooted in insufficient health capital basic survival endowment—within a complex framework encompassing social, economic, cultural, institutional, and environmental dimensions (Li et al., 2023). Deficits in health capital trigger cascading socioeconomic challenges: first, unmet healthcare needs exacerbate financial burdens, leading to medical impoverishment and catastrophic health expenditures (Zhao et al., 2020); second, health deprivation restricts educational and occupational opportunities, perpetuating inequities and obstructing social mobility (Niessen et al., 2018); third, diminished health capital erodes labor productivity, income stability, and healthcare access, undermining individual resilience and self-sufficiency (Bor et al., 2017). Consequently, the multidimensionality of health poverty renders it susceptible to macro-societal shifts, including economic transitions, demographic aging, epidemiological changes, health-focused poverty interventions, and healthcare resource allocation. The aggregation of individual or household-level health poverty ultimately manifests as spatially entrenched regional health disparities.

Since China's reform and opening-up, pronounced spatial heterogeneity in healthcare coverage, economic development, and environmental conditions across its 34 provincial-level regions has resulted in uneven health poverty outcomes(Lai et al., 2023). Eastern regions, benefiting from polarization effects during early economic reforms, rapidly overcame health poverty and began radiating trickle-down effects to central and western regions (Alder et al., 2016; Tao and Wang, 2020). However, persistent geographical disparities and policy inertia have precluded nationwide convergence, with regional heterogeneity remaining a defining feature of health poverty. Moreover, macro-level societal transformations—economic restructuring, population aging, healthcare demand shifts, and environmental governance—diffuse through regional systems, reshaping social ecosystems and indirectly modulating health outcomes via pathways such as economic status, lifestyle behaviors, and environmental exposures (F. Chen et al., 2010; H. Liu et al., 2014; Zhao, 2023). China's rapid urbanization and urban expansion have had profound implications for public health, potentially exacerbating health-related poverty. Urban expansion contributes to the loss of ecosystem services through intra-, peri-, and tele-coupling mechanisms, leading to environmental degradation and increased health risks (Kong et al., 2025). Concurrently, urbanization reduces individuals' exposure to nature—including the frequency, duration, and intensity of such exposure—which can impair mental health, diminish social cohesion, and decrease physical activity (Cox et al., 2018). These transformations disrupt established lifestyles, widen health disparities, and intensify health-related poverty, particularly among vulnerable populations. In the post-poverty-eradication era, multidimensional health poverty—characterized by deprivation in health rights, capability deficits, and risk accumulation due to economic constraints, inequitable resource distribution, and environmental degradation—has emerged as a critical impediment to consolidating poverty alleviation achievements and advancing sustainable development. Thus, analyzing the spatiotemporal impacts of macroeconomic transitions, aging demographics, healthcare utilization patterns, and environmental governance on provincial health poverty is imperative.

The spatial and temporal heterogeneity of health-related poverty in China is reflected not only in regional disparities of the overall Health Poverty Index (HPI), but also in two core scientific questions addressed by this study: (1) Does heterogeneity exist in the dynamic evolution of both the incidence (i.e., the breadth of poverty coverage) and depth (i.e., the severity of poverty) of health-related poverty? (2) Do the driving factors (such as economic development and healthcare resources) exhibit spatiotemporal differentiation in their effects on health-related poverty?

This study investigates the spatiotemporal distribution and driving mechanisms of health poverty across China's provincial regions over a decade. Its contributions are twofold: first, we construct a novel health poverty index (HPI) integrating health rights, health capabilities, and health risks, measured using 10-year provincial panel data. Second, employing spatiotemporal geographically weighted regression (GTWR), we reveal the heterogeneous spatial and temporal effects of drivers, providing evidence for tailored anti-poverty strategies to achieve universal health coverage and eradicate health poverty.

Methods

Overview. Existing research has conceptualized health poverty through three primary lenses, each of which presents inherent measurement limitations that impede a comprehensive understanding of the phenomenon:

Health poverty as substandard physiological health. The first perspective defines health poverty as a condition in which an individual's health status falls below a minimum threshold, such as having a body mass index (BMI) outside the World Health Organization (WHO) standards or experiencing physical deterioration due to illness (Kim et al., 2023; Kou and Yasin, 2024; Nawaz, 2021; Parra-Mujica et al., 2024; Simões et al., 2016). Notably, scholars such as Clarke and Erreygers (2020) have articulated this view, emphasizing physiological outcomes (Clarke and Erreygers, 2020). Measurement limitations: This definition reduces health poverty to singular physiological indicators (e.g., disease presence, BMI levels). By focusing exclusively on biological outcomes, it neglects the holistic WHO definition of health as "a state of complete physical, mental, and social well-being."Consequently, it fails to capture non-physiological aspects of deprivation, including mental health deficits and social isolation(WHO, 1948). Thus, such measurements are overly narrow, portraying health as a purely biological construct rather than a multidimensional state.

Health Poverty as Medical Impoverishment. The second, and more widely adopted, perspective characterizes health poverty as the descent of household disposable income below the poverty line as a result of healthcare expenditures (K. Chen, Hu, et al., 2024; Iqbal and Nawaz, 2017; H. Jia et al., 2022; Ma et al., 2022; Sterck et al., 2018), often measured by indicators such as catastrophic health spending or medical-induced impoverishment (Y.-C. Kong et al., 2022; Li et al., 2012; Xu et al., 2003). Measurement limitations: This framework adopts an exclusively economic lens, equating health poverty with the financial burden of healthcare. While it effectively quantifies the economic impact of illness, it overlooks crucial non-economic dimensions of health deprivation, such as limited access to preventive care, low health literacy, or unmet mental health needs. Measurements are therefore confined to economic factors (e.g., out-of-pocket expenditure) and fail to reflect the broader spectrum of health-related vulnerabilities.

Health Poverty as a Dimension of Multidimensional Poverty. The third approach situates health poverty as a component within multidimensional poverty, shaped by the interaction between physiological health, economic status, education, employment, and various social factors(K. Chen, Qiu, et al., 2024; Jun and Sutton, 2024; Mokdad et al., 2015; Xiong et al., 2024; Zou and Cheng, 2023). Drawing on Sen's capability deprivation theory, this perspective is frequently operationalized through the Alkire-Foster method (developed by OPHI), which integrates health within broader poverty assessments(Miletzki and Broten, 2017). Measurement limitations: Although multidimensional, this approach treats health as a subsidiary dimension of poverty rather than centering on health itself. Measurements tend to prioritize poverty dynamics over the intrinsic attributes of health, such as health rights (e.g., access to social security) or health capabilities (e.g., ability to seek care). Additionally, macro-social policies (e.g., healthcare resource allocation) and micro-environmental factors (e.g., pollution) are often overlooked, limiting the capacity of these measures to fully capture the complexity of health poverty.

Collectively, these frameworks and measurements exhibit four fundamental shortcomings: Overly narrow scope: By relying on single dimensions (physiological or economic), these definitions fail to encompass health's holistic nature, which includes physical, mental, and social well-being. Neglect of health-specific constructs: Current measures often overlook health rights (e.g., insurance coverage), capabilities (e.g., health literacy), and risk accumulation (e.g., behavioral or environmental risks), which are central to the concept of health poverty. Subordination of health to poverty: Multidimensional approaches frequently reduce health to a mere component of poverty, rather than treating it as an independent and dynamic phenomenon with its own determinants. Inattention to context and dynamics: Few measurements account for spatiotemporal heterogeneity or the interplay between individual health and macro-level factors (e.g., demographic aging, environmental governance), despite the spatially entrenched nature of health disparities.

These gaps underscore the need for a more comprehensive, health-centered measurement framework—one that integrates rights, capabilities, and risks while accounting for dynamic, context-specific determinants.

Conceptualizing Health Poverty: A Theoretical Framework of Its Three Core Dimensions

Core Concept of Health Poverty. We define health poverty as a condition precipitated by disease and health risks, leading to a sustained depletion of health endowments and resources, which traps individuals in a cycle of declining economic capacity and increasing burdens. This situation diminishes or eliminates personal development opportunities and capabilities, resulting in relative deprivation of resources and rights, constituting a state of poverty and deprivation initiated by health loss. By moving beyond the limitations of traditional, single-dimensional physiological or economic perspectives, this concept emphasizes that health poverty originates from insufficient health capital and manifests as a multidimensional phenomenon. Specifically, it encompasses economic poverty (impoverishment due to medical expenses), capability poverty (restricted development opportunities), and rights poverty (unequal access to resources), all of which are further compounded by the interplay between health risks and institutional factors.

The Three Dimensions of Health Poverty: Health Rights, Health Capabilities, and Health Risks. Drawing on the concept of health poverty as proposed in this paper, we further elucidate its theoretical foundations, which are principally informed by Amartya Sen's Capability Deprivation Theory, the World Health Organization's Social Determinants of Health framework, and prominent theories of health risk. From these perspectives, we identify three core dimensions of health poverty: health rights, health capabilities, and health risks, each described as follows:

Health rights refer to macro-level interventions that empower individuals through institutional frameworks and supportive social conditions, thereby addressing limitations in personal health capabilities. The importance of health rights was recognized as early as 1948 in the Universal Declaration of Human Rights, which identified the right to health as essential for ensuring individual physical well-being.

Health capabilities constitute the fundamental endowments necessary for human survival and represent the primary deficits underlying the emergence of health poverty. These capabilities are reflected in individuals' physiological health status, healthcare needs, intrinsic health literacy and skills, capacity to access external resources, and the collective resilience and mutual support of their communities. The lack of adequate health capabilities generates a negative feedback loop between disease and poverty, serving as the root cause of health poverty.

Health risks encompass dynamic and uncertain factors that contribute to the onset, perpetuation, and deepening of health poverty. These risks include individual biological and genetic vulnerabilities, self-imposed risk behaviors, environmental hazards, and social exclusion resulting from deficiencies in social networks and institutional protection.

Methodological Framework for Constructing a Health Poverty Index. The construction of the health poverty index in this paper refers to the measurement method of the global Multidimensional Poverty Index (MPI) and mainly includes four core steps: parameter setting, health poverty identification, aggregation, and decomposition(Alkire and Foster, 2011; Foster, 2009).

Parameter Setting for Multidimensional Health Poverty Measurement. In the parameter setting, the deprivation threshold serves as a criterion to assess whether a household experiences health poverty in each indicator. The deprivation thresholds in this study are based on national authoritative standards and questionnaire design details, fully considering the characteristics of the data and the real-world context of social development. For the weight allocation across dimensions and indicators, the equal weighting method used by the global MPI was adopted. This approach facilitates consistent analysis of cross-period data, helps depict the dynamic evolution trend of overall health poverty, and ensures the comparability of the index across different periods.

Multidimensional Health Poverty Identification. Health poverty identification involves determining whether a household is deprived or experiences health poverty in each indicator. Based on the deprivation status of each household in every indicator, combined with the indicator weights, the total deprivation score of the household is calculated. If the total deprivation score exceeds the multidimensional health poverty threshold k, it indicates that the household is experiencing multidimensional health poverty. The specific steps are as follows:

Let n represent the total number of sample households, y_{ij} represent the value of household i on indicator j, z_j $(z_j > 0)$ represent the threshold or poverty line for the j-th indicator. For any y_{ij}, a deprivation matrix $g_{ij}^0 = \left[g_{ij}^0\right]$ can be defined, where the element g_{ij}^0 is defined as: when $y_{ij} < z_j$, $g_{ij}^0 = 1$; when $y_{ij} > z_j$, $g_{ij}^0 = 0$. For example, for the ij element, if household i is deprived in the j dimension (such as education), it is assigned a value of 1; if not deprived, it is assigned a value of 0.

LetW_j represent the weight of each indicator. For the deprivation matrix g_{ij}^0, calculate the total deprivation score of households i across all indicators, i.e., Ci $=\sum_{j=1}^{a} W_j g_{ij}^0$. Meanwhile, let k be the threshold for judging multidimensional health poverty, with values ranging from 0 to 1. If Ci>k, household i is considered multidimensionally health poor and is assigned a value of 1; if Ci <k, household i is not considered multidimensionally health poor and is assigned a value of 0. In this study, k is set to 1/3.

Aggregation of Multidimensional Health Poverty. Based on the identification of multidimensional health poverty for all households, the following indicators can be calculated:

Incidence of Health Poverty: $H = q/n$; the proportion (expressed as a percentage) of the population who are multidimensionally health poor. It is sometimes called the 'poverty rate' or 'headcount ratio'.

Depth of Multidimensional Health Poverty: $A = \frac{\sum_{i=1}^{n} Ci(k)}{qd}$; the average percentage of weighted indicators in which poor people are deprived – that is, the average deprivation score among poor people.

$$\text{Health Poverty Index} : \text{HPI} = \text{H} \times \text{A}.$$

Here, *q* is the number of households in multidimensional health poverty; *n* is the total number of households; *d* is the total number of indicators; *i* represents any household; *k* is the threshold for identifying multidimensional health poverty; *Ci* is the deprivation score of households *i* under the threshold *k*.

Decomposition of Health Poverty. The Health Poverty Index (HPI) can be decomposed by dimensions, urban-rural areas, provinces, etc. Taking the urban-rural decomposition as an example, let *u* represent the urban data matrix, *r* represents the rural data matrix, and *z* represent the deprivation threshold for any indicator. Then:

$$\text{HPI}(u, r, z) = \frac{n(u)}{n(u, r)} \text{HPI}(u; z) + \frac{n(r)}{n(u, r)} \text{HPI}(r; z)$$

In summary, the HPI developed in this study synthesizes the core concerns of existing measurement approaches, addressing their limitations in terms of unidimensionality, outcome orientation, and insufficient attention to intrinsic mechanisms. This results in a more nuanced and authentic measurement system that better captures the essence of health poverty and provides a more precise tool for analyzing its spatiotemporal dynamics.

Data Sources. This study utilizes six waves of data (2010, 2012, 2014, 2016, 2018, and 2020) from the China Family Panel Studies (CFPS), a nationally representative longitudinal survey conducted by the Institute of Social Science Survey (ISSS) at Peking University. The CFPS tracks individuals, households, and communities to comprehensively document social, economic, demographic, educational, and health-related transformations in China(Z. Zhou et al., 2021). Building on the conceptual framework of health poverty, which encompasses health rights, health capabilities, and health risks, we extracted individual- and household-level data on demographics, health status, educational attainment, lifestyle habits, and economic conditions. Key indicators include participation in pension and medical insurance, chronic disease prevalence, years of education, smoking and alcohol consumption, internet access, and catastrophic health expenditures (Table 1). Following cross-wave data matching, missing values were addressed through imputation and rigorous cleaning procedures, resulting in a final sample of 76,999 households (Fig. S1).

Indicators and variable selection. Drawing on the methodology of the Multidimensional Poverty Index (MPI), we constructed a household-level Health Poverty Index (HPI) using equal weighting across three dimensions: health rights (access to social security), health capabilities (access healthcare), and health risks (behavioral factors). This study employs an equal weighting scheme for all dimensions and indicators, a practice widely adopted in multidimensional poverty and health poverty research (Alkire et al., 2022; Chi et al., 2022; Jia et al., 2022). Although this approach may, to some extent, obscure the relative importance of specific dimensions in determining overall health poverty at different periods, it minimally affects the depiction of overall health poverty trends and enhances the comparability of the index. Furthermore, the equal weighting method transcends the traditional unidimensional perspective- focused solely on physiological health or economic poverty- and facilitates a more comprehensive understanding of the intrinsic mechanisms of health poverty from a multidimensional and egalitarian perspective.

Deprivation cutoffs for each indicator were aligned with China's contextual realities and international standards (Alkire and Foster, 2011; Foster, 2009). Provincial HPI values, ranging from 0 to 1, with higher values indicating greater deprivation, were derived by aggregating household-level indices annually from 2010 to 2020. For detailed theoretical explanations of the three core dimensions and their associated indicators, see Appendix 1.1.

Guided by prior studies on health poverty drives and provincial data availability, we selected seven key indicators as explanatory variables for the Geographically and Temporally Weighted Regression (GTWR) model (Table 2). These encompass macroeconomic, demographic, healthcare, and environmental factors, detailed in Appendix 2.

Spatiotemporal geographically weighted regression model. Traditional ordinary least squares (OLS) regression, while useful for identifying global relationships between variables, fails to account for spatiotemporal non-stationarity, the phenomenon where relationships vary across space and time—and overlooks the unique influence of geographical context on health poverty. To address this limitation, we turn to methods that explicitly model spatial and temporal heterogeneity. Grounded in Waldo R. Tobler's First Law of Geography ("Everything is related to everything else, but near things are more related than distant things" (Tobler, 1970), Brunsdon and Fotheringham (1996)

Table 1 Parameter settings for health poverty measurement.

Dimension	Indicator	Deprivation threshold	Weight
Health rights	Whether family members are enrolled in medical insurance	If any family member lacks medical insurance, it is considered deprivation and assigned a value of 1.	1/9
	Whether family members are enrolled in pension insurance	If any adult family member lacks pension insurance and does not receive a pension, it is considered deprivation and assigned a value of 1.	1/9
	Whether the household has experienced catastrophic health expenditure	If the household experiences catastrophic health expenditure, it is considered deprivation and assigned a value of 1.	1/9
Health capacities	Whether family members suffer from chronic diseases	If one family member suffers from ≥2 chronic diseases or ≥2 family members each suffer from one chronic disease, it is considered deprivation and assigned a value of 1.	1/12
	Whether family members have access to the internet	If no one in the household has access to the internet, it is considered deprivation and assigned a value of 1.	1/12
	Annual per capita income of the household	If the annual per capita income of the household is below the national poverty line, it is considered deprivation and assigned a value of 1.	1/12
	Educational attainment of family members	If the average years of education for adults in the household are less than 6 years or if school-age children are out of school, it is considered deprivation and assigned a value of 1.	1/12
Health risks	Smoking status of family members	If any family member has smoked within the last month, it is considered deprivation and assigned a value of 1.	1/9
	Alcohol consumption status of family members	If any family member consumes alcohol ≥3 times per week, it is considered deprivation and assigned a value of 1.	1/9
	Body Mass Index (BMI) of family members	If there is moderate or severe thinness or obesity among children and adolescents in the household, or if adults are underweight or obesity, it is considered deprivation and assigned a value of 1.	1/9

pioneered the geographically weighted regression (GWR) model, a nonparametric approach that captures spatial non-stationarity by allowing regression coefficients to vary geographically (Brunsdon et al., 1996). Similarly, the temporally weighted regression (TWR) model incorporates temporal coordinates to assess time-varying effects (Que et al., 2020). Building on these foundations, the spatiotemporal geographically weighted regression (GTWR) model integrates both spatial and temporal dimensions, enabling coefficients to vary across space and time (Huang et al., 2010). By optimizing spatiotemporal bandwidths and weight matrices, GTWR identifies region-specific and time-specific relationships, offering a nuanced understanding of how drivers of health poverty evolve dynamically. Compared to GWR and TWR, GTWR provides a more comprehensive framework for analyzing spatiotemporal heterogeneity.

In this study, we systematically compared OLS, TWR, GWR, and GTWR models to identify the optimal approach for characterizing the spatiotemporal drivers of health poverty. The GTWR model formulated as follows:

$$Y_i = \beta_0(u_i, v_i, t_i) + \textstyle\sum_k \beta_k(u_i, v_i, t_i) X_{ik} + \varepsilon_i;$$

$$i = 1, \ldots \ldots, n.$$

where Y_i denotes the HPI in spatiotemporal unit i (indicating a province in a certain year), X_{ik} represents the independent variables, k denotes the total number of spatiotemporal units, ε_i is the random error term in spatiotemporal unit i, (u_i, v_i, t_i) represents the spatiotemporal coordinates of sample i, $\beta_0(u_i, v_i, t_i)$ denotes the intercept in spatiotemporal unit i, and $\beta_k(u_i, v_i, t_i)$ denotes the local coefficient of X_{ik} in spatiotemporal unit i. Adaptive kernel and Akaike Information Criterion were also used in the GTWR model for the kernel function. Formulas for OLS, TWR, and GWR are provided in Appendix 3.

Results

Measurement of national health poverty in China, 2010–2020. Table 3 presented the HPI, incidence, and depth across Chinese households under varying deprivation thresholds ($k = 0$ to $k = 0.7$) from 2010 to 2020. As the threshold k increased, both the HPI and incidence declined, while the depth of poverty intensified, with both HPI and incidence approaching near-zero levels at $k = 0.7$. Between 2014 and 2020, the most pronounced reductions in health poverty incidence occurred when k increased from 0.2 to 1/3, with declines of 23.3%, 26.3%, 26.7%, and 25.9%, respectively, indicating $k = 1/3$ as a critical threshold. Aligning with international MPI standards and ensuring cross-year comparability, we selected $k = 1/3$ as the optimal cutoff. (Alkire and Santos, 2014) At this threshold, the HPI decreased from 0.338 in 2010 to 0.163 in 2020, and incidence dropped from 68.5% to 37.9%. The depth of health poverty also improved, declining by 0.065 overall, with the steepest reductions observed between 2012 and 2014. Additionally, we tested the robustness of the HPI under unequal weighting using the entropy method, which validated the reliability of the main findings. The results of the robust analysis were presented in Appendix 4.1 (Table S1 and S2).

Spatiotemporal patterns of provincial health poverty in China. Provincial HPI data revealed significant spatial disparities (Table 4). In 2010, the top three HPI rankings were occupied by western provinces, specifically Guizhou (0.503), Guangxi (0.427), and Yunnan (0.406), while Beijing (0.192) and Shanghai (0.222) recorded the lowest values. By 2020, Guizhou (0.241) and Beijing (0.056) retained their positions as the highest and lowest HPI regions, respectively. From 2010 to 2020, western provinces such as Guizhou (0.360), Guangxi (0.306), and Sichuan (0.303) recorded the highest mean HPI values, whereas eastern regions like Beijing (0.132) and Shanghai (0.157) exhibited the lowest. Regionally, the severity of health poverty ranked as follows: Western > Northeastern/Central > Eastern. Intraregional heterogeneity was most pronounced in the West (variation: 0.142), followed by the East (0.129). Notably, all provinces achieved HPI reductions between 2010 and 2020. Seven provinces, including Tianjin (East), Jiangxi (Central), and Guangxi, Guizhou, Yunnan, Gansu (West), experienced declines exceeding 0.2, with Guizhou showing the largest drop (0.262). Spatiotemporal visualizations of provincial HPI were provided in Appendix 4.2 (Fig. S2).

Further analysis indicated significant spatiotemporal heterogeneity in both the incidence and depth of health poverty across

Table 2 Factors influencing province's health poverty index and indicator selection.

Dimension	Indicator	Label	Source	Unit	Previous research supports
Economic development	Per capita GDP	X1	China Statistical Yearbook	10,000 yuan	Bor et al., 2017 ; Fisher et al., 2021
Population structure	Old-age dependency ratio	X2	China Statistical Yearbook	%	Rodriguez Ruzafa et al., 2022; Zhou et al., 2023
	Illiterate population aged 15+	X3	China Population and Employment Statistical Yearbook	%	Hunn et al., 2023; Banerjee et al., 2021
Healthcare resource	Government health expenditure percentage	X4	China Health Commission Statistical Yearbook	%	Wagstaff et al., 2018; Atun et al., 2015
	Registered nurses per 1000 population	X5	China Health Commission Statistical Yearbook	individual	Luo et al., 2024; Tang et al., 2021
Environmental pollution	PM2.5 concentration over three years	X6	Atmospheric Composition Analysis Group	$\mu g/m^3$	Rentschler and Leonova, 2023; Ssekibaala and Kasule, 2023
Healthcare needs	Outpatient visits per resident	X7	China Health Commission Statistical Yearbook	visits	Li and Lin, 2024; Liu et al., 2023

Table 3 Measurement of health poverty index.

Threshold for health poverty	Health poverty index					
	2010	2012	2014	2016	2018	2020
$k = 0.1$	0.407	0.388	0.342	0.309	0.289	0.259
$k = 0.2$	0.393	0.369	0.318	0.282	0.260	0.227
$k = 1/3$	0.338	0.312	0.256	0.214	0.192	0.163
$k = 0.4$	0.281	0.255	0.195	0.152	0.131	0.106
$k = 0.5$	0.158	0.148	0.099	0.070	0.058	0.044
$k = 0.6$	0.095	0.090	0.051	0.033	0.025	0.016
$k = 0.7$	0.029	0.290	0.013	0.008	0.005	0.003
Threshold for	Health poverty incidence %					
health poverty	2010	2012	2014	2016	2018	2020
$k = 0.1$	97.5%	95.6%	93.9%	92.4%	90.7%	87.2%
$k = 0.2$	88.4%	84.0%	78.2%	74.1%	70.3%	63.8%
$k = 1/3$	68.5%	63.3%	54.9%	47.8%	43.6%	37.9%
$k = 0.4$	52.6%	47.5%	37.8%	30.0%	26.3%	21.4%
$k = 0.5$	25.7%	23.9%	16.4%	11.8%	9.9%	7.7%
$k = 0.6$	14.0%	13.3%	7.7%	4.9%	3.8%	2.5%
$k = 0.7$	3.8%	3.8%	1.7%	10.0%	0.7%	0.4%
Threshold for	Depth of health poverty					
health poverty	2010	2012	2014	2016	2018	2020
$k = 0.1$	0.418	0.405	0.364	0.334	0.319	0.297
$k = 0.2$	0.444	0.439	0.406	0.381	0.37	0.356
$k = 1/3$	0.494	0.494	0.467	0.449	0.441	0.429
$k = 0.4$	0.534	0.537	0.517	0.506	0.5	0.493
$k = 0.5$	0.617	0.619	0.604	0.595	0.588	0.58
$k = 0.6$	0.675	0.674	0.668	0.662	0.656	0.653
$k = 0.7$	0.77	0.759	0.77	0.763	0.757	0.746

provinces (Appendix 4.3, Table S3 and S4). Regarding regional disparities, the average incidence (0.632, 0.616) and average depth (0.507, 0.468) in western provinces (e.g., Guizhou, Yunnan) were notably higher than those in eastern regions (average incidence: 0.474; average depth: 0.446). These western provinces also experienced more substantial decreases in health poverty, with Guizhou, for instance, showing a reduction of 0.371 in incidence and 0.102 in depth. In contrast, Shanghai experienced a marked decline in incidence from 0.496 to 0.251 (a decrease of 0.245), while its depth only slightly decreased from 0.448 to 0.430 (a decrease of 0.017). Temporally, the period from 2014 to 2016 saw the most pronounced reductions in both incidence and depth; for example, Tianjin's incidence decreased by 0.108, and Hunan's depth by 0.082.

Spatiotemporal heterogeneity of health poverty drivers: GTWR analysis

Model comparison: OLS, TWR, GWR, and GTWR. To evaluate spatiotemporal non-stationarity, we compared four regression models: Ordinary Least Squares (OLS, global), Temporally Weighted Regression (TWR, temporal), Geographically Weighted Regression (GWR, spatial), and Geographically and Temporally Weighted Regression (GTWR, spatiotemporal). The baseline OLS results, and the results of the multicollinearity tests were shown in Table 5.

Table 5 presented the results of the global OLS regression, indicating that X1, X3, X6, and X7 were not statistically significant predictors. This lack of significance suggested spatial heterogeneity in the determinants of health poverty, as the associations between these variables and the Health Poverty Index (HPI) might not have been uniform across regions. Furthermore, a multicollinearity test using the variance inflation factor (VIF) showed that all variables had VIF values below 6, confirming the absence of severe collinearity. The insignificance of these variables in the global OLS model highlighted the need to employ the

Table 4 Provincial decomposition measurement of the health poverty index from 2010 to 2020.

Region	Province	2010	2012	2014	2016	2018	2020	HPI change	Mean value	
Northeastern China	Liaoning	0.286	0.254	0.231	0.205	0.205	0.171	-0.115	0.225	0.256
	Jilin	0.393	0.319	0.315	0.280	0.247	0.227	-0.166	0.297	
	Heilong jiang	0.35	0.31	0.269	0.212	0.182	0.155	-0.195	0.246	
Eastern China	Beijing	0.192	0.214	0.133	0.103	0.094	0.056	-0.136	0.132	0.215
	Tianjin	0.324	0.287	0.225	0.161	0.186	0.088	-0.236	0.212	
	Hebei	0.368	0.339	0.27	0.213	0.197	0.179	-0.189	0.261	
	Shanghai	0.222	0.182	0.156	0.148	0.127	0.108	-0.114	0.157	
	Jiangsu	0.342	0.322	0.28	0.213	0.195	0.166	-0.176	0.253	
	Zhejiang	0.283	0.263	0.221	0.175	0.167	0.128	-0.155	0.206	
	Fujian	0.345	0.318	0.241	0.223	0.216	0.175	-0.17	0.253	
	Shandong	0.322	0.29	0.227	0.194	0.165	0.161	-0.161	0.227	
	Guangdong	0.316	0.333	0.233	0.197	0.189	0.151	-0.165	0.237	
Central China	Shanxi	0.311	0.281	0.243	0.214	0.179	0.149	-0.162	0.230	0.235
	Anhui	0.314	0.323	0.260	0.196	0.161	0.159	-0.155	0.236	
	Jiangxi	0.403	0.349	0.312	0.250	0.226	0.180	-0.223	0.287	
	Henan	0.367	0.325	0.247	0.212	0.213	0.186	-0.181	0.258	
	Hubei	0.261	0.226	0.204	0.166	0.147	0.131	-0.130	0.189	
	Hunan	0.304	0.28	0.219	0.197	0.161	0.121	-0.183	0.214	
Western China	Guangxi	0.427	0.36	0.347	0.261	0.231	0.209	-0.218	0.306	0.287
	Chongqing	0.331	0.325	0.289	0.226	0.203	0.152	-0.179	0.254	
	Sichuan	0.384	0.389	0.324	0.281	0.248	0.192	-0.192	0.303	
	Guizhou	0.503	0.468	0.366	0.312	0.269	0.241	-0.262	0.360	
	Yunnan	0.406	0.394	0.321	0.231	0.220	0.187	-0.219	0.293	
	Shaanxi	0.348	0.245	0.236	0.191	0.138	0.147	-0.201	0.218	
	Gansu	0.404	0.375	0.307	0.239	0.185	0.155	-0.249	0.278	

Table 5 Global OLS regression results.

Variable	Parameter estimate	t-statistic	*p* value	Standard error	VIF
Interception	40.38049	11	0.000	3.182872	—
X1	-0.5116595	-1.83	0.069	0.2796995	5.59
X2	-0.3019731	-2.520	0.013	0.1197235	1.63
X3	0.0917922	0.470	0.642	0.1970069	1.96
X4	0.1890616	2.310	0.023	0.0820095	2.12
X5	-5.78849	-8.04	0.000	0.7198332	3.01
X6	-0.0497494	-1.6	0.111	0.0310187	1.23
X7	0.3650658	0.98	0.329	0.3723868	3.95
R^2			0.743		
RSS				2282.700	
AICc				850.053	

Table 6 Comparison of evaluation metrics and parameters for global OLS, TWR, GWR, and GTWR models.

Model evaluation metrics	OLS	TWR	GWR	GTWR
R-squared (R^2)	0.743	0.877	0.897	0.920
Residual sum of squares (RSS)	2282.700	1269.290	1070.830	828.708
Corrected Akaike Information Criterion (AICc)	850.053	822.167	811.390	796.253
regression standard error (Sigma)	—	2.909	2.672	2.350

GTWR model, which was better suited to capturing local and dynamic effects, thereby revealing the spatiotemporal non-stationarity in the relationships between the variables and the HPI. (The results of the two-way fixed effects model in Appendix 5.1 also indicate the presence of spatiotemporal non-stationarity among the variables).

Model performance was assessed using R^2, residual sum of squares (RSS), corrected Akaike Information Criterion (AICc), and regression standard error (Sigma) (Table 6). GTWR outperformed all models, achieving the highest R^2 (0.920), lowest RSS (828.708), lowest AICc (796.253), and smallest Sigma (2.350). GWR ($R^2 = 0.897$) and TWR ($R^2 = 0.877$) followed, while OLS ($R^2 = 0.743$) exhibited the weakest fit. These results confirmed GTWR's superior capacity to capture spatiotemporal heterogeneity, justifying its use for subsequent analysis. The GTWR coefficient statistics were detailed in Appendix 5.1 (Table S5).

Regression results of the GTWR model. To precisely analyze the spatiotemporal evolution and spatial differentiation of regression coefficients for factors influencing the HPI from 2010 to 2020 (Fig. 1), and considering the connection between China's HPI dynamics and the Targeted Poverty Alleviation (TPA) campaign,

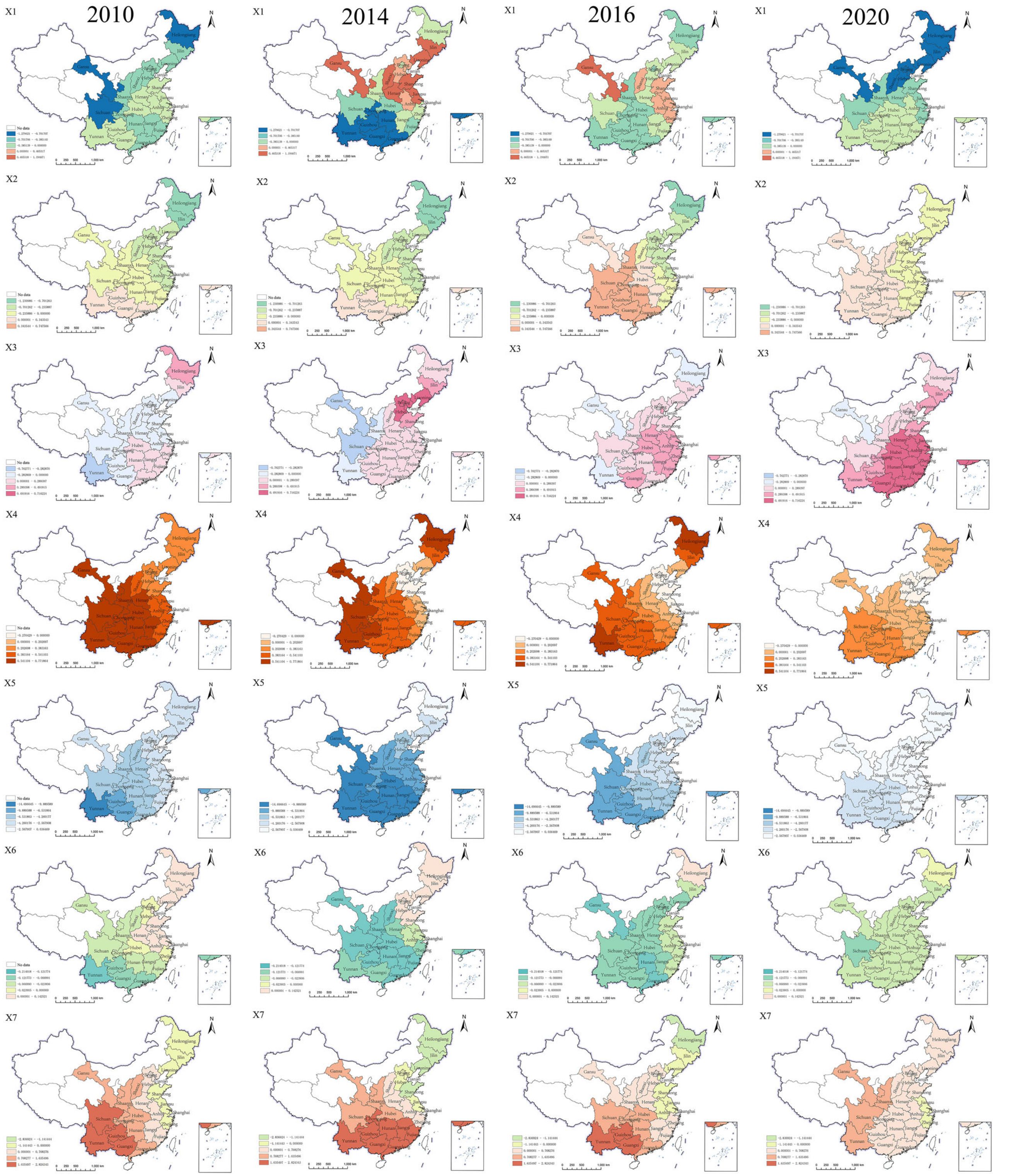

Fig. 1 Regression coefficients of the GTWR model. The series of maps illustrates the regression coefficients for variables X1 to X7 across the years 2010, 2014, 2016, and 2020, arranged from left to right. The maps were generated under cartographic license number GS (2023)2767, issued by the Ministry of Natural Resources of the People's Republic of China. The basemap remains unchanged, and areas shown in white represent regions with missing data. Note: The color scale for each year is set independently based on the actual range of regression coefficients for that year, to facilitate the display of spatial variation within the year. Cross-year comparisons should be based on numerical values rather than color intensity.

four critical time nodes were selected: 2010 (pre-TPA implementation), 2014 (TPA initiation), 2016 (2 years post-TPA), and 2020 (eradication of absolute poverty). These time points encompassed the entire process of China's poverty eradication efforts and incorporated broader sociodemographic shifts to comprehensively reveal the spatiotemporal variation patterns of influential factors at key milestones, thereby enhancing the understanding of the evolving mechanisms underlying health poverty.

X1 (Per capita GDP): X1 generally exhibited a negative effect on HPI, characterized by significant temporal dynamics and spatial heterogeneity. In 2010, high negative coefficients were concentrated in Gansu, Sichuan, and Heilongjiang provinces, with moderate-to-high negative impacts in northern contiguous regions and southern provinces such as Hunan, Jiangxi, Guangdong, and Fujian. By 2014, the high negative values shifted to western regions like Yunnan, Guizhou, and Guangxi. By 2016, the extent of high negative coefficients stabilized, but their absolute magnitudes declined, indicating a weakening effect. By 2020, a nationwide negative association between per capita GDP and HPI was evident, with the absolute coefficient values decreasing from north to south, and northeastern and northern provinces re-emerged as areas of high negative coefficients.

X2 (Old-age Dependency Ratio): This variable revealed a southwest-northeast spatial dichotomy, with positive coefficients in southwestern provinces (e.g., Yunnan, Guizhou) and negative coefficients in northeastern provinces (e.g., Liaoning, Jilin). Temporally, its coefficients showed an upward trend nationwide, with expanding spatial coverage of positive effects. The peak positive effect occurred between 2014 and 2016, followed by a decline in 2020; however, spatial polarization remained evident.

X3 (Illiterate Population Aged 15+): Over time, this variable showed expanding positive effects, with influence decreased from southeast to northwest. In 2010, core positive-impact areas were in eastern and northeastern China. By 2014–2016, positive effects extended to over half of the provinces, with high-value clusters shifted to the Beijing-Tianjin-Hebei and Yangtze River Delta regions. By 2020, all provinces exhibited positive coefficients, with the highest values in southeastern China, reflected persistent educational disparities in China's poverty dynamics.

X4 (Government Health Expenditure Percentage): This variable demonstrated strong positive spatial autocorrelation but declining temporal coefficients. High-positive clusters persisted in southwestern provinces such as Sichuan, Chongqing, Yunnan, and Guizhou. Since 2014, negative coefficients emerged in Beijing-Tianjin-Hebei and Shandong, approaching zero by 2020. Regions with higher health poverty consistently correlated with larger positive coefficients.

X5 (Registered nurses per 1000 population): X5 predominantly exerted negative effects, with absolute coefficients weakened from southwest to northeast. Temporally, an initial increase peaked in 2014, followed by post-2020 decline in both coefficient magnitudes and interprovincial disparities.

X6 (3-year PM2.5 concentration): X6 exhibited predominantly negative associations, transitioning from early mixed coefficients to stable negative effects. Negative-impact areas displayed a "southwest-northeast" distribution, with greater negative in central-western regions. Absolute coefficients peaked in 2014–2016 before declined by 2020, paralleling China's air quality governance progress.

X7 (Outpatient visits per resident): Coefficients for X7 showed a "west-positive vs. east-negative" gradient. positive coefficients dominated central-western provinces, while negative clusters emerged in northeastern and eastern regions (e.g., Jiangsu, Zhejiang, Shanghai). Spatial patterns remained stable until 2016, with negative clusters contracting to the Yangtze River Delta by 2020, accompanied by reduced interprovincial disparities, reflected regional healthcare accessibility gaps documented in China's health system reforms.

Discussion

Spatiotemporal evolution of health poverty in China from 2010 to 2020. From 2010 to 2020, China experienced a significant improvement in health poverty. The Health Poverty Index (HPI) declined from 0.338 in 2010 to 0.163 in 2020, and the incidence dropped from 68.5% to 37.9%. However, the depth of health poverty changed minimally, decreasing by only 0.065%, which aligns with the findings of Jia (H. Jia et al., 2022). At the provincial level, rapid declines in HPI and incidence in regions such as Guizhou and Yunnan reflect the "high baseline, rapid improvement" pattern characteristic of western provinces. Conversely, areas like Shanghai demonstrate a pattern of "substantial reduction in incidence but limited alleviation in depth," highlighting a challenge in some developed eastern regions where it is "easier to reduce prevalence than intensity." Overall, the most concentrated reductions in health poverty occurred between 2014 and 2016, coinciding with the implementation of intensified national health poverty alleviation policies during this period.

In western provinces, health poverty alleviation policies have effectively reduced incidence, but persistent resource constraints increase vulnerability to the disease-poverty-disease cycle. Previous research has shown that rates of catastrophic health expenditures and illness-induced poverty are significantly higher in western regions than in the east, which largely explains the persistent depth of health poverty in these areas (Jia et al., 2023; Zhen et al., 2018). In contrast, in economically developed eastern provinces such as Shanghai, inadequate social security coverage for marginalized groups may account for the stable depth of health poverty. Prior studies have confirmed that migrant workers and informal employees in developed provinces face disadvantages in medical insurance participation and access to health services (Guan, 2017; Khan et al., 2021).

The spatiotemporal evolution of health poverty in China thus reflects not only broad regional disparities, characterized by "high baseline and rapid improvement," but also local variations marked by "asynchronous alleviation of breadth and depth." This dual characteristic underscores the importance of balancing regional coordination with targeted policies in the governance of health poverty.

Economic development as a key driver of health poverty reduction across provinces. The inverse relationship between X1 and health poverty exhibited clear temporal dynamics and spatial variation. From 2010 to 2020, economic growth significantly alleviated health poverty in most provinces, although its marginal effect diminished over time. Economic development produced trickle-down and spillover effects, improving healthcare access, elderly care, and public infrastructure, and thereby enhancing health outcomes (Cen and Yan, 2022; Niu et al., 2021; Wang et al., 2014). However, as economic progress continued, diminishing returns appeared. Countervailing factors, such as climate change and chronic disease burdens (Egger, 2011), partially offset the gains from poverty reduction (Monnot, 2017). The temporal decrease in X1's coefficients reflected China's achievements in poverty alleviation, especially in southwestern provinces targeted by the TPA policy.

Spatially, the areas most negatively affected by X1 shifted to the southwest in 2014 and returned to some northern provinces by 2020. This shift was consistent with targeted poverty alleviation efforts in key southwestern regions (Guo et al., 2018; Xu et al., 2021). In these core TPA areas, health poverty was effectively reduced through economic development, which focused on strengthening health capabilities and improving access to healthcare services (Dai et al., 2020; Qi et al., 2022; X. Wang and Ye, 2024). For instance, poverty rates in Sichuan, Chongqing, Yunnan, and Guizhou fell from 9.6%, 6.0%, 17.8%, and 21.3% in 2013 to 0.3%, 0.12%, 1.32%, and 0.85% by 2019, respectively (Zhang et al., 2022). By 2020, however, higher coefficients in northeastern and northern provinces highlighted structural challenges, such as dependence on heavy industry, population outflow, and economic stagnation, which exacerbated health poverty (Hu and Lin, 2013; You et al., 2021).

X6 showed similar spatiotemporal patterns to X1, highlighting the link between economic growth and environmental degradation. (Li et al., 2016; Zhang et al., 2020) In line with the Environmental Kuznets Curve (EKC) (Stern, 2004), early industrialization worsened pollution, but later economic innovation helped mitigate environmental harm (Munasinghe, 1999; Stern et al., 1996). This underscores the necessity for industrial upgrading and innovation-driven growth to balance economic welfare with health capital preservation.

Under the economic development dimension, variables X1 (economic development) and X6 (environmental pollution) demonstrate significant spatiotemporal linkage effects. In 2014, southwestern provinces experienced both a strong negative effect of X1 (indicating that economic growth alleviates health poverty) and a strong negative effect of X6 (indicating that pollution exacerbates health poverty), highlighting a paradox wherein poverty alleviation relied on resource-based economic growth, resulting in an "economic improvement–pollution aggravation" dilemma. By 2020, the northeastern region saw a resurgence of the negative effect of X1 and a weakening of the negative effect of X6, suggesting that industrial transformation contributed to synergistic improvements in "economy–environment–health." This interaction implies that the mitigating effect of economic development on health poverty must be considered in conjunction with regional industrial structure and environmental governance capacity: eastern regions achieve a win–win scenario for economy and environment through innovation-driven development, whereas western regions must balance growth with pollution control.

Spatiotemporal heterogeneity of health poverty under demographic transitions. From 2010 to 2020, X2 demonstrated an increasingly significant positive effect on the health poverty index, with its geographical influence steadily expanding. This pattern correlates with China's demographic shift toward an aging population. By 2020, individuals aged 65 and over accounted for 13.5% of the population, and the old-age dependency ratio rose to 19.7%—increases of 4.63 and 7.80 percentage points, respectively, compared to 2010 (Tu et al., 2022). Furthermore, single-child families, a result of the family planning policies of the 1990s, are now assuming greater eldercare responsibilities, which may intensify caregiving burdens and reinforce health poverty vulnerabilities (Lu et al., 2024). Spatial analysis reveals that X2's influence is most pronounced in southwestern China, where underdeveloped economies, lower disposable incomes, inadequate savings, and insufficient elderly care security systems increase the region's susceptibility to aging-related health poverty.

The rising societal emphasis on educational attainment has heightened health poverty risks among populations with low literacy. Our results indicate that by 2020, X3 exhibited a widespread positive correlation with the health poverty index, with both its geographic reach and intensity increasing over time. Limited education constrains illiterate populations through multiple barriers, including restricted access to essential resources, challenges in obtaining health information, poor health literacy, and difficulties in adopting healthy behaviors (Thengal, 2013). These limitations lead to inadequate disease prevention, inefficient healthcare utilization, and inequitable health rights (DeWalt et al., 2004). Paradoxically, X3's effects are stronger in economically developed eastern provinces with advanced technological infrastructure. The emphasis on technological innovation and service automation in these regions may unintentionally exacerbate barriers to resource access for illiterate groups, potentially increasing social exclusion among vulnerable populations (Hong et al., 2017; Ragnedda, 2018).

Given the dual challenges of digital transformation and population aging, China requires tailored, province-specific policy frameworks to address health poverty. In eastern regions, digital platforms should be leveraged for real-time health poverty monitoring and risk alerts. Central regions should strengthen grassroots healthcare and integrate chronic disease management. Western regions need to prioritize internet infrastructure and medical assistance to break cycles of health poverty. Northeastern regions should develop elderly care markets and intelligent assessment systems for disabled seniors. This differentiated "one-province-one-policy" approach can help construct a spatially optimized framework for health poverty alleviation.

Within the population structure dimension, the interaction between X2 (population aging) and X3 (low education level) exhibits a "regional differentiation–effect stacking" characteristic. In the southwest, the positive effects of X2 (aging exacerbates health poverty) and X3 (low education exacerbates health poverty) produced a cumulative impact, with both coefficients rising simultaneously in Guizhou and Yunnan from 2014 to 2016, reflecting the dual demographic pressures of "aging + low education." In contrast, the northeast benefited from higher social security coverage and relatively balanced educational resources, as evidenced by the negative effect of X2 and the low positive effect of X3. This interaction suggests that the impact of population structure on health poverty must be considered alongside regional education levels and pension security: the east should leverage digital technologies to bridge the educational divide among the elderly, while the west should prioritize improvements in basic education and elderly care services.

Patterns of provincial health poverty mitigation in healthcare service utilization. Our analysis reveals that regions with higher health poverty indices tend to have higher coefficients for X4; however, this positive association has weakened over time. This decline is associated with more efficient allocation of governmental health expenditures. Historically, provincial health spending in China prioritized curative services over preventive care, resulting in inefficient resource use (Yip et al., 2012). Following healthcare reforms, expenditure priorities shifted toward efficiency, improving the targeting of medical resources, supporting primary healthcare, reducing operational costs, and minimizing systemic waste. These changes have enhanced the effectiveness of public health investments in alleviating poverty (Wang and Tao, 2019; Yip et al., 2019). Spatial analysis reveals that X4 has a stronger positive impact in southwestern China, where underdeveloped areas are more dependent on government health spending to address financial constraints and health poverty. Therefore, future policies should both increase health expenditures in disadvantaged regions and improve efficiency metrics to maximize the government's impact on health poverty reduction.

The density of registered nurses (X5) significantly reduces health poverty risks by improving healthcare accessibility and service quality. The mitigating effect of X5 decreases from southwest to northeast, mirroring the uneven geographic distribution of medical resources in China (Lu et al., 2021). Over the study period, the impact of X5 followed an inverted U-shaped pattern, with regional disparities narrowing after 2016. Substantial investments in healthcare resources in southwestern and northwestern regions between 2014 and 2016—driven by targeted poverty alleviation initiatives and the Health Poverty Eradication Project—advanced healthcare decentralization and strengthened the poverty-reducing effect of X5 (Huang et al., 2023; Zhu et al., 2024). In contrast, X7 displays a "western high-eastern low" coefficient pattern. Residents of less developed central and western provinces face higher risks of catastrophic health expenditure due to limited financial resilience, increasing their vulnerability to health poverty (Jia et al., 2023). Notably, interprovincial disparities in X7's effects declined from 2010 to 2020, likely due to the 2016 integration of urban and rural medical insurance, which raised reimbursement thresholds and reduced disease-related financial burdens in underdeveloped regions (Yang et al., 2018).

For the healthcare resource dimension, the interactions among X4 (healthcare expenditure), X5 (nurse shortages), and X7 (outpatient needs) reveal regional differences in "resource allocation–demand satisfaction" adaptability. In southwestern provinces, the high positive effect of X4 (increased expenditure yet persistent health poverty) and the strong negative effect of X5 (nurse shortages aggravate poverty) indicate a structural contradiction of "inefficient investment–manpower shortage," while the positive effect of X7 (increased outpatient visits accompanying poverty) highlights weak healthcare payment capacity. In contrast, the eastern region displays a favorable interaction, with negative effects for X4, X5, and X7, reflecting "abundant resources–efficient utilization." This interaction suggests that healthcare resources must be aligned with regional demand characteristics to alleviate health poverty: the west should strengthen primary-level human resource allocation, while the east should optimize expenditure structures to enhance service accessibility.

Limitations

First, the biennial survey design of the CFPS database limits the ability to analyze provincial health poverty dynamics on an annual basis between 2010 and 2020. Second, despite the multidimensional nature of health poverty, data availability limitations necessitated the selective inclusion of determinant variables. Third, the associations identified between variables and HPI using GTWR in this study represent statistical correlations within the spatiotemporal context. It is not possible to entirely rule out reverse causality or the impact of omitted variables. Therefore, caution should be exercised to avoid over-interpreting these associations, and our conclusions should remain limited to descriptive analysis and mechanistic exploration. Finally, this study utilizes provincial administrative units as the spatial analysis unit, and the ratio of the sample size to the number of independent variables may affect model performance, with a potential risk of overfitting. Our global VIF results and spatiotemporally consistent, interpretable coefficient patterns provide confidence that multicollinearity does not unduly influence our results. But developing standardized local diagnostics for GTWR remains a valuable future methodological endeavor.

Conclusion

This study contributes to health poverty research through three key innovations. First, it develops an HPI that integrates health rights, capabilities, and risks, thereby addressing the limitations of traditional single-dimensional measures. Second, by employing GTWR, the study uncovers spatiotemporal heterogeneity in health poverty: economic growth most effectively alleviated poverty in Southwest China during 2014–2016, but its impact diminished in subsequent years; aging and low educational attainment exhibited polarized regional effects; and the influence of pollution decreased with improved governance. Third, the study bridges micro-level deprivation with macro-level transitions, highlighting that the evolution of health poverty in China is characterized by significant interregional disparities—namely, a "high baseline, rapid improvement" pattern—alongside local "asynchronous breadth-depth alleviation." These findings underscore the necessity for both regional coordination and targeted interventions, such as workforce expansion in the west, a focus on equity in the east, and aging-adapted reforms in the northeast, thereby offering valuable insights for advancing global health equity.

Data availability

The data used in this paper to construct the Health Poverty Index and its influencing factors were obtained from various public databases, such as the China Family Panel Studies (CFPS, isss.pku.edu.cn/cfps/) and the public database of China's National Bureau of Statistics(https://www.stats.gov.cn/sj/). If researchers need to use the processed dataset of this study, please contact the corresponding author to obtain it.

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Author contributions

Ye Li: Conceptualization, funding acquisition, investigation, writing—original draft, writing—review and editing. Fangqi Qu: Methodology, formal analysis, supervision, validation. Yulu Tian: Data curation, formal analysis, software, visualization. Rui Chen: Formal analysis, software, validation, visualization. Yongqiang Lai: Conceptualization, data curation, formal analysis, methodology, project administration, writing—original draft, Writing—review and editing. All authors have read and approved the final manuscript.

Competing interests

The authors declare no competing interests.

Ethical approval

The data used in this study are from CFPS (2010–2020), whose ethical review is overseen by the Peking University Biomedical Ethics Committee. The CFPS project has a unified ethical approval number: IRB00001052-14010, with annual continuing reviews conducted. Initial Ethical Approval: Obtained on January 2014, with a unified and permanent approval number: IRB00001052-14010. This study's data use complies with the original approval standards, with no additional interventions involving human subjects.

Informed consent

During CFPS data collection, adults signed written informed consent; guardians signed on behalf of minors (oral consent required for those over 10 years old). Respondents' information has been anonymized, and the data used in this study contains no personally identifiable content. Records of informed consent implementation are archived by the Institute of Social Science Survey, Peking University for verification. For CFPS 2010, 2012, 2014, 2016, 2018, and 2020 waves: Informed consent was collected in the corresponding survey years in line with the project's annual data collection schedule.

Additional information

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