Environmental Health Engineering and Management Journal. 2026;13:1682
http://ehemj.com
doi 10.34172/EHEM.1682

Environmental Health Engineering and Management Journal

Original Article

Open Access Publish Free

The Spatial Effects of CO_2 Emissions on the Quality of Healthcare Services: Evidence from Iranian Provinces

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Abstract

Background: The economic toll of health issues related to carbon emissions is substantial, accounting for a significant portion of national healthcare expenditures. This research addresses the lack of studies on healthcare service quality and the local effects of carbon emissions.

Methods: This study employed spatial econometrics to investigate the direct and indirect effects of carbon emissions on the quality of health services across Iranian provinces from 2011 to 2021. This method was chosen for its ability to capture both within-province and between-province effects, which is crucial for developing robust health policies. The researchers created a comprehensive index for health service quality, incorporating input, output, and overall index, using the entropy method.

Results: The findings indicate that CO_2 pollutants negatively impact both the output and the overall health service quality index. Economic growth demonstrated a positive direct impact and a negative indirect (spillover) effect on both dependent variables. The divergent indicators of direct and geographical consequences of per capita output growth imply a multifaceted link between the two. This indicates that economic affluence in one province directly enhances the quality of its healthcare services. The quality of health services in nearby regions may suffer as a result. Moreover, the input index demonstrates a substantial positive effect, while inflation and inequality exhibit a detrimental effect on the quality of health services.

Conclusion: The study's findings suggest that improving the quality of health services requires a multifaceted approach, encompassing not only direct healthcare investments but also broader economic and environmental considerations.

Keywords: Health services, Environmental pollutants, Iran

Citation: Keshavarz H, Hosseinzadeh R, Bakhshi R, Khademi Kolahloo A, Sadeghi R. The spatial effects of CO_2 emissions on the quality of healthcare services: evidence from Iranian provinces. Environmental Health Engineering and Management Journal. 2026;13:1682. doi: 10.34172/EHEM.1682.

Article History:
Received: 16 July 2025
Revised: 24 September 2025
Accepted: 6 October 2025
ePublished: 28 January 2026

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Introduction

Greenhouse gas emissions, particularly carbon dioxide (CO_2) emissions, are among the most significant environmental challenges of the current century. The rise in atmospheric CO_2 levels not only precipitates climate change but also engenders widespread health problems, thereby diminishing the quality of health and medical services (1). Policy priorities within any society direct the allocation of resources. In the developmental trajectory of developing economies and drawing from the experiences of various nations, diverse policies are considered (2), a prominent example of which can be examined within the context of the global system and playing a role in international trade. Within the modern capitalist system, environmental degradation coupled with failures in providing public goods constitutes one of the main challenges for multinational corporations and international trade. The need to maximize profit compels multinational corporations to disregard external costs, such as environmental pollution and the destruction of natural resources. This approach not only harms environmental welfare but also threatens public access to essential goods like clean air, safe water, and stable ecosystems. Due to inadequate regulations, industrial activities in developing countries lead to environmental damage and greenhouse gas emissions. The failure to internalize environmental costs in market operations represents an economic failure directly linked to inequalities in resource distribution (3). Given the current circumstances, examining CO_2 emissions in conjunction with the quality of health and medical services emerges as a key priority.

CO_2 emissions are continuously increasing, compelling global health systems to respond dynamically to counteract this trend. Research indicates that 3.6 billion people worldwide currently reside in regions highly vulnerable to climate change. It is projected that between 2030 and 2050, climate change alone will cause approximately 250,000 additional deaths annually due to malnutrition, malaria, diarrhea, and heat stress (4). Elevated levels of atmospheric CO_2 directly compromise human health. Medical experts concur on three major health impacts of high emission levels: respiratory problems, headaches, and impaired cognitive functions. These direct consequences impose additional pressure on health institutions to deliver services (5,6).

The health market differs from other markets due to market failures arising from asymmetric information between patients and providers, moral hazards caused by health insurance, and the classification of some health services as public goods. Health is considered both a capital good, as individuals invest in it through healthcare services, nutrition, and physical activity to enhance productivity, and a consumption good, as it directly improves quality of life (7). Poverty, education level, and access to healthcare are key determinants of health, and non-communicable diseases remain major challenges (8). Environmental stress influences immune function through the nervous and endocrine systems (9). Given the role of health systems in ameliorating the effects of greenhouse gas emissions, there is increasing emphasis on sustainable practices to improve health outcomes and reduce environmental degradation costs (10,11). Preventive actions against emissions, alongside strengthening health systems, are essential for maintaining food security and preventing physical and mental development disorders (12). Climate change has expanded disease vectors such as mosquitoes and ticks, increasing malaria and dengue cases, while extreme weather events disrupt food production, leading to malnutrition and foodborne diseases (13,14). Thus, health systems face dual challenges: mitigating the health impacts of climate change and reducing their own greenhouse gas emissions (15).

The emission of greenhouse gases in various industrial, agricultural, urban, and building sectors has significant and indirect impacts on health and the quality of healthcare services. The increase in CO2 concentration leads to climate changes and phenomena such as rising temperatures and air pollution, which increase the burden of diseases and place additional pressure on the healthcare system (16,17). Studies have shown that pollution caused by CO_2 increases the incidence of cardiovascular and respiratory diseases and significantly raises hospital admissions (18,19).

Climate change can also affect healthcare infrastructure and reduce the efficiency of health systems. Heatwaves resulting from climate change increase hospital energy consumption for ventilation and cooling, and in many cases, cause disruptions in the functioning of medical equipment and raise operational costs (20,21). Therefore, reducing CO_2 emissions in the industrial and urban sectors is important not only from an environmental perspective but also as a fundamental strategy for preserving and improving the quality of public health services.

The lack of attention in existing studies to a quality index for health and medical services and a provincial-level examination of the effects of carbon dioxide emissions on these services, and the neglect of spatial effects, provided the intellectual impetus for the present study. The objective of this research was to investigate the impact of CO_2 emissions on the quality of health and medical services using spatial econometric techniques. This methodology was chosen because, in addition to direct (intra-regional) effects, it can also account for indirect or spillover (inter-regional) effects. This capability can be instrumental in formulating more effective and comprehensive health sector policies.

The framework of this study is organized as follows: The first section reviews the theoretical and empirical literature on emissions and their impact on the health sector, evaluating existing theories and studies to identify and apply an appropriate theoretical framework. The second section outlines the research model and estimation methods employed to test the research hypotheses. The third section focuses on the examination of the results. Finally, the fourth section presents the conclusions and recommendations.

Material and methods

Data and research model

Based on the presented theoretical foundations, the factors influencing the quality of health services (QHS) can be examined under three broad categories: economic, social, and institutional-political. The conceptual model of factors affecting QHS is based on the resources that underpin health service delivery. Data about QHS include the number of physicians and nurses per capita, the number of hospital beds, the number of rehabilitation facilities, and the number of pharmacies, which are considered as input variables for the health sector (Input Index of Quality of Health Services, QHS_{INP}). These factors can be evaluated within the institutional context of the health sector. Conversely, the outcomes of QHS, derived from output variables such as the infant mortality rate (under 1 year), the proportion of the population over 65 years, and the number of registered deaths in a year, constitute social factors within this domain and are estimated in the Output Index of QHS (Output Index of Quality of Health Services, QHS_{OUT}). The QHS index, encompassing input, output, and a comprehensive measure, has been estimated using the entropy method.

The stages of index construction, as outlined by Saisana and Commission (22), include policy relevance, simplicity, validity, consideration of time-series data, availability of affordable data, sensitivity, and reliability. However, the most contentious aspect of index construction lies in determining the weights.

Weighting methods can be broadly categorized into subjective and objective approaches (23). One prominent objective method is the entropy method. Given that this research aimed to evaluate the quality of health and medical services based on real and measurable data, objective methods that rely on statistical data were preferred over subjective methods, which depend on individual judgment and opinion. Especially in the healthcare domain, where performance data are readily available, the use of subjective methods can lead to bias and reduced validity of the results.

Among objective index construction methods such as CRITIC (Criteria Importance Through Intercriteria Correlation) (24), PCA (Principal Component Analysis) (25), and the entropy method (26), the entropy method was employed in this study. Compared to methods like CRITIC, which also consider the correlation between indicators, the primary objective of the current research was not to control for correlation but rather to identify indicators with the highest discriminatory power among units. Since entropy focuses on the amount of information and the dispersion of data, it was deemed preferable to the CRITIC method for this purpose. Furthermore, in contrast to methods like PCA, the entropy method directly extracts indicator weights, thereby avoiding the complexities associated with analyzing latent components. PCA is more suitable for dimensionality reduction and extracting hidden components rather than directly weighting indicators for index construction, whereas entropy directly calculates indicator weights.

First, the data were normalized due to differences in data scales, the elimination of measurement units, the avoidance of large value bias, and the unification of the direction of influence according to equation (1). This equation states that higher values have a more favorable situation:

$$r_{ij} = \frac{x_{ij} - min(x_{ij})}{\max(x_{ij}) - min(x_{ij})} \tag{1}$$

where x_{ij} represents the value of the i-th index in the j-th year. The next step is to use the standardized values for quantifying the fluctuations using the entropy method, which is done through equations (2) and (3):

$$E_{ij} = -\frac{1}{\ln(n)} \sum\nolimits_{j=p_{ij}}^{n} \ln(p_{ij}) \tag{2}$$

$$p_{ij} = \frac{r_{ij}}{\sum\nolimits_{j=}^{n} r_{ij}} \tag{3}$$

where P_{ij} is the value of the index over the sum of the index values, and E_{ij} indicates the amount of entropy for the i-th index. Finally, the weight and the mentioned index are obtained according to equations (4) and (5):

$$W_i = \frac{-E_i}{\sum\nolimits_{i=}^{n} (-E_i)} \tag{4}$$

$$S_j = \sum_{i=}^{n} W_i \times r_{ij} \tag{5}$$

where W_i is the weight of the i-th indicator, and S_j represents the composite indicator in the j-th year.

To ensure the credibility of the indexation performed using the entropy method, it is appropriate to perform indexation using another method as well. The Principal Component Analysis (PCA) method is used for indexation and data dimension reduction. PCA helps us design a composite of principal components for indexation (25,27). The weight assigned to each component is based on the maximum variance and correlation structure. Therefore, we expect variables with higher variance to have greater weight.

Similar to the entropy method, the assigned weights are determined based on the maximum information, which makes it suitable for comparison with the entropy method. To begin, data normalization is required. We normalize the data using the same approach as Equation 1 for the entropy method. Then, indexation is performed according to the equation below. After normalization, the covariance matrix of the normalized matrix Z is calculated according to Equation 6:

$$Z^t Z \big/ n \quad 1 \quad C \tag{6}$$

$$|\lambda \mathrm{I} - C| = 0 \,. \tag{7}$$

Using Equation 7, we calculate the **eigenvalues** (λ), which represent the amount of variance explained by each component (I is the identity matrix). To estimate the explained variance, we use Equation 8.

$$Explained\,Variance\,Ratio = \lambda_i \Big/ \sum\nolimits_{j=1}^{p} \lambda_j \times 100 \tag{8}$$

For each eigenvalue λi, we have an eigenvector ei, which represents the variable weights in the i-th component. Multiplying each element of this vector by the variables under consideration for indexing yields the principal components (PC).

Based on the entirety of the theoretical underpinnings and extant studies (27–29), econometric models 9 and 10 are examined:

$$OVE_{it} = \beta_1 LPC_{it} + \beta_2 PLGDP_{it} + \beta_3 INP_{it} + \beta_4 INF_{it} + \beta_5 JC_{it} + \beta_6 EDU_{it} + \theta_{it} \tag{9}$$

$$OUT_{it} = \alpha_1 LPC_{it} + \alpha_2 PLGDP_{it} + \alpha_3 INP_{it} + \alpha_4 INF_{it} + \alpha_5 JC_{it} + \alpha_6 EDU_{it} + \varepsilon_{it} \tag{10}$$

The analysis necessitated the implementation of two key indices: QHS_{INP} and QHS_{OUT}. Subsequently, after the computation of these two indices, the overall Quality of Health Services index (QHS_{OVE}) was estimated.

According to Hosseinzadeh (2023), CO_2 emissions for each year in every province were calculated based on the consumption volume of each fossil fuel, which was extracted from Iran's energy balance sheet. By multiplying the consumption of each fuel by its respective carbon dioxide emission factor, the amount of carbon emission attributable to each type of fossil fuel per year was determined. Ultimately, the sum of carbon emissions of all fuels was calculated for one province. This procedure was carried out for all provinces (31 provinces) (30). Table 1 provides the definition of variables:

Model estimation method

The methodology employed in this study is spatial econometrics. A prerequisite for employing this method is the existence of spatial correlation among variables. This correlation occurs when the values of a variable in one region are influenced by other variables in adjacent regions. Moran's test is used to test the existence of dependence between regions (31).

The general spatial econometric model used is presented as shown in Equations (11) and (12).

$$Y = \delta WY + X\beta + WX\theta + \alpha l_N + \mu \tag{11}$$

$$\mu = \lambda W_u + \varepsilon \tag{12}$$

In the above equation, Y is an $N \times 1$ vector of the dependent variable, and X denotes an $N \times K$ matrix comprising K explanatory variables. W is the spatial weight matrix, and β is a $K \times 1$ vector of direct effect coefficients. Furthermore, WY represents the interaction effects among the dependent variable (spatial lag of the dependent variable), WX represents the interaction effects of the independent variables (spatial lags of explanatory variables), and Wu represents the interaction effects among the disturbance components (spatially autocorrelated error term). ρ is the spatial autoregressive coefficient (for WY), θ is the vector of coefficients for WX (spillover effect coefficients), and λ is the spatial error coefficient, representing spillover effects through the disturbance term (32).

There are different methods for creating a spatial weight matrix. In this study, the proximity method was used to create this matrix because the proximity matrix provides a better description of the location of the provinces of Iran than the distance matrix.

Based on the above equation (general form), three model types can be defined, including the spatial error model (SEM), the spatial Durbin model (SDM), and the spatial autoregression model (SAR). After confirming the existence of spatial correlation in the data using the Moran test, the next step is to select the best model among the different spatial models using the two Wald and multiple Wald tests. Finally, the spatial Hausman test is used to choose between fixed effects and random effects in panel data models.

Results

Healthcare Service Quality Index

In accordance with the Shannon entropy method introduced in the indexation section, it is necessary to validate the weights assigned to the three indices—input, output, and the overall Quality of Health Services (QHS) index. This is done by comparing the calculated weights with those derived from an alternative method, Principal Component Analysis (PCA).

The QHS input and output variables (introduced in the "Data and Research Model" section) were first normalized using the min-max method (Equation 1). A normalized value for each variable was then obtained for every province in each year under study. Given that the entropy method determines weights based on the dispersion of the variables (Equations 2 and 3), validation requires examining the weights in relation to the variables' fluctuations. We expect higher weights to be assigned to

Table 1. definition of variables

Variable	Definition	Source	Expected sign
QHS_{OVE}	The overall Quality of Health Services index was calculated using the entropy method.	Research calculations based on "Statistical Center of Iran data"	
QHS_{Out}	The output Quality of Health Services index is calculated using the entropy method.	Research calculations based on "Statistical Center of Iran data"	
QHS_{INP}	Input Quality of Health Services index was calculated using the entropy method.	Research calculations based on "Statistical Center of Iran data"	+
LPC	Carbon dioxide emissions in each province in tons	Research calculations based on Iran's Energy Balance	−
PLGDP	Value-added growth rate per capita for each province	Statistical Center of Iran data	+
INF	Consumer Price Index Growth Rate in Each Province	Statistical Center of Iran data	−
JC	Gini coefficient	Statistical Center of Iran data	−
EDU	Higher education graduates	Statistical Center of Iran data	+

Source: Extraction based on literature review variables with greater fluctuations.

PCA also analyzes weights, but the weights are derived from the importance of each indicator within each component and the component's contribution to the total variance. In effect, PCA assigns a higher weight to greater variance. Microsoft Excel was used for the entropy calculation, and EViews and Excel were used for the PCA.

In accordance with Equations 6 to 8, the indexation is performed using the Principal Component Analysis (PCA) method. The estimates for the principal components (PCs) are calculated and presented in accordance with the estimated eigenvalues in Table 2.

Table 2 presents the eigenvalue for each component for the two indices: QHS_{INP} (input) and QHS_{OUT} (output). For the QHS_{OUT} index, the first component has an eigenvalue of 1.7 and explains 57% of the total variance. The second component has an eigenvalue of 0.84, accounting for 28% of the variance, and the third component, with an eigenvalue of 0.44, explains 14% of the variance. Regarding the QHS_{INP} index, the first component has an eigenvalue of 1.74 and explains approximately 43.6% of the total variance. The second component covers 26.9% of the variance with an eigenvalue of 1.07. Cumulatively, the first two components explain about 70% of the variance, and with the addition of the third component, this figure rises to nearly 89%. Therefore, a substantial portion of the data's information is explained by the first three components.

Table 3 presents the loadings (or weights) of each variable on the principal components. For instance, within the components forming the QHS_{INP} index, variable 1 exhibits the highest loading on the second component (0.91), while variable 2 loads more heavily on the first component (0.57). Similarly, variable 3 has a high loading on the first component (0.62). These loadings indicate that each principal component is a linear combination of the original variables, and they show which variables contribute most significantly to its formation. For interpretation, a component with high loadings on several variables is typically considered a proxy for those variables. Such an analysis can also be carried out for OUTPUT variables 1 to 3.

The principal components (PC1, PC2, etc.) are linear combinations of the original variables, constructed to be orthogonal and to capture the maximum amount of data variance sequentially. Their values, ranging from 1 to 3 for the output index and 1 to 4 for the input index, are provided in Table 2. The loadings in Table 3 demonstrate the magnitude and direction of each variable's contribution to each PC. Consistent with the explanatory power of the variance, for the final PCA-based index construction, we ultimately use PC1 as the basis for the index calculations. The functional reasons for the performance of the variables in each of the input and output indices can also be linked to their covariance matrix (Table 4).

To examine internal consistency and monitor the coherence of the index's components, we can use Cronbach's alpha (33). Alpha values of 0.93 and 0.61 were obtained for the QHS input and output variables, respectively. An alpha value between 0.6 and 0.7 indicates a marginal level of internal consistency, while a value between 0.7 and 1 suggests good internal consistency. Therefore, the constituent variables are considered to

Table 2. The eigenvalues of the components constituting the output and input QHS indices

Index	Number	Value	Difference	Proportion	Value	Proportion
Output	1	1.713393	0.867276	0.5711	1.713393	0.5711
	2	0.846118	0.405629	0.282	2.559511	0.8532
	3	0.440489	---	0.1468	3	1
Input	1	1.743963	0.669279	0.436	1.743963	0.436
	2	1.074683	0.337408	0.2687	2.818646	0.7047
	3	0.737276	0.293197	0.1843	3.555922	0.889
	4	0.444078	---	0.111	4	1

***Source**:* Research calculations

Table 3. Loadings of variables on principal components (eigenvectors (*λ*))

Index	Variable number	Variable	PC 1	PC 2	PC 3
Output	1	Proportion of the population over 65 years	0.598535	−0.505134	0.621768
	2	Number of registered deaths in a year	0.658844	−0.131136	−0.740762
	3	Infant mortality rate (under 1 year)	0.45572	0.85302	0.254315
Input	1	Number of physicians and nurses per capita	−0.13215	0.916272	0.113753
	2	Number of hospital beds	0.575885	0.376904	−0.346695
	3	Number of rehabilitation facilities	0.510778	−0.024907	0.859106
	4	Number of pharmacies	0.624499	−0.1333	−0.358886

***Source**:* Research calculations

Table 4. Variable correlation structure for PCA

Index	Variable	Proportion of the population over 65 years	Number of registered deaths in a year	Infant mortality rate (under 1 year)	
Output	Proportion of the population over 65 years	1			
	Number of registered deaths in a year	0.528828	1		
	Infant mortality rate (under 1 year)	0.172422	0.336813	1	
		Number of physicians and nurses per capita	**Number of hospital beds**	**Number of rehabilitation facilities**	**Number of pharmacies**
Input	Number of physicians and nurses per capita	1			
	Number of hospital beds	0.107289	1		
	Number of rehabilitation facilities	−0.07348	0.289112	1	
	Number of pharmacies	−0.196268	0.472288	0.326332	1

Source: Research calculations

have a satisfactory level of internal consistency. To assess the validity of the entropy-based index, we compared it with an index derived from the Principal Component Analysis (PCA). The results revealed a 99.5% correlation for QHS_{OUT} and a 78% correlation for QHS_{INP}. Given that the overall index is a weighted average of the QHS input and output indices, a combined correlation of approximately 90% was found. Based on these results, the calculated entropy-based index has the necessary internal consistency and validity for the inter-provincial analysis of health and medical service quality.

The provided map (Figure 1) illustrates the distribution of the Healthcare Service Quality Index across the country's provinces, calculated and depicted using the entropy method. As observed on the map, the index values for each province are numerically displayed, and provinces are categorized into five distinct color ranges based on these values. Green indicates provinces with higher service quality, white represents average quality, and red signifies provinces with lower healthcare service quality. This classification facilitates a quicker understanding of health status and the distribution of regional inequalities in service provision.

Yaghmaeian et al's analysis confirms our results. In the output index, the total index presented in Figure 1 shows that Tehran and Isfahan, as the case studies, are not in a favorable condition. Additionally, South Khorasan is in a favorable condition in the output index (34).

Choosing the appropriate model

Table 5 presents the results of the Moran, Wald, multiple Wald, and spatial Hausman tests. Based on Moran's test results, the existence of a spatial relationship between the data is confirmed. According to the Wald tests, the SDM is more appropriate than the SAR model. Similarly, considering the results of the multiple Wald test, the probability level *p*-value is close to zero, thus the SDM is more suitable than the SEM. This implies that the best model is the SDM.

Following the determination of the appropriate model, the final step involves selecting the type of effects in the spatial panel data (fixed effects or random effects). The results of the spatial Hausman test show that the random effect model is more appropriate than the fixed effect model. Therefore, the final model should be estimated as a random effects SDM model.

Table 5. The tests of the spatial model

Test typ	Coefficient	Prob.
Moran's test	−0.29	0.06
Wald test for choosing between SEM and SDM	15.56	0.00
Wald test: Choosing between SAR and SDM	24.32	0.00
Spatial Hausman test	6.12	0.46

Source: Research calculations

The estimation results of the Spatial Durbin Model (SDM) with random effects are presented in Table 6. Based on the table, the coefficient of the spatial effects is significant in both models. This indicates that the Quality of Healthcare Services in one region can be influenced by the Quality of Healthcare Services in its neighboring regions. Accordingly, the control of greenhouse gas emissions at the national level should be enhanced through inter-regional environmental cooperation, and tailored regional policies should be formulated to control carbon dioxide emissions.

Based on Table 6, the direct impact coefficients of PLGDP on Quality of Healthcare Services are 0.08 and 0.23 in the two models, respectively. This indicates that a one percent increase in per capita production growth leads to an increase in both overall Quality of Healthcare Services (OVE) and output Quality of Healthcare Services (QHS_{OUT}) within the regions. Higher income levels in provinces directly enhance the financial capacity for investing in healthcare infrastructure and providing health and medical services. Furthermore, individuals residing in areas with higher economic growth typically have higher income levels. Their increased per capita income enables greater per capita expenditure on health insurance schemes, improved access to medications, and

Table 6. SDM model estimation results

Effects	Variables	Model II	Model I
		Coefficient	Coefficient
Intra-regional effect	*PLGDP*	0.06 **	0.19 ***
	LPC	−0.07 ***	−0.1 **
	QHS_{INP}	0.55**	0.016 **
	INF	−0.025*	−0.01
	JC	−0.11 *	−0.24 **
	EDU	0.07**	0.021*
Inter-regional effect	W × *PLGDP*	−0.01 ***	0.045
	W × *LPC*	0.07	0.061
	W × QHS_{INP}	0.04	−0.02
	W × *INF*	−0.003	−0.012
	W × *JC*	−0.017	0.045*
	W × *EDU*	0.053*	0.045

***Significance level 1%
** Significance level 5%
* Significance level 10%
Source: Research calculations

more desirable necessary treatments. However, its indirect effect on the quality of health services is negative. The studies by Deaton (33) and Qin et al (34) reached similar results. Economic growth significantly affects the speed of convergence of medical resources, and heterogeneity among provinces also has a considerable impact on the convergence of medical resources.

The direct effect of LPC in models one and two is −0.09 and −0.12, respectively, and both are statistically significant. This coefficient indicates that a one percent increase in carbon emissions in a region leads to a 0.09% and 0.12% decrease in QHS_{OVE} and QHS_{OUT} within that region. The indirect and spatial coefficients of LPC are not significant in either model. An increase in disease prevalence due to LPC emissions can place significant strain on the healthcare system. The rising demand for healthcare services can push the capacity of existing health facilities, leading to shortages of beds, equipment, and personnel. These results were also presented in a study by Abed Al Ahad, which showed that long-term

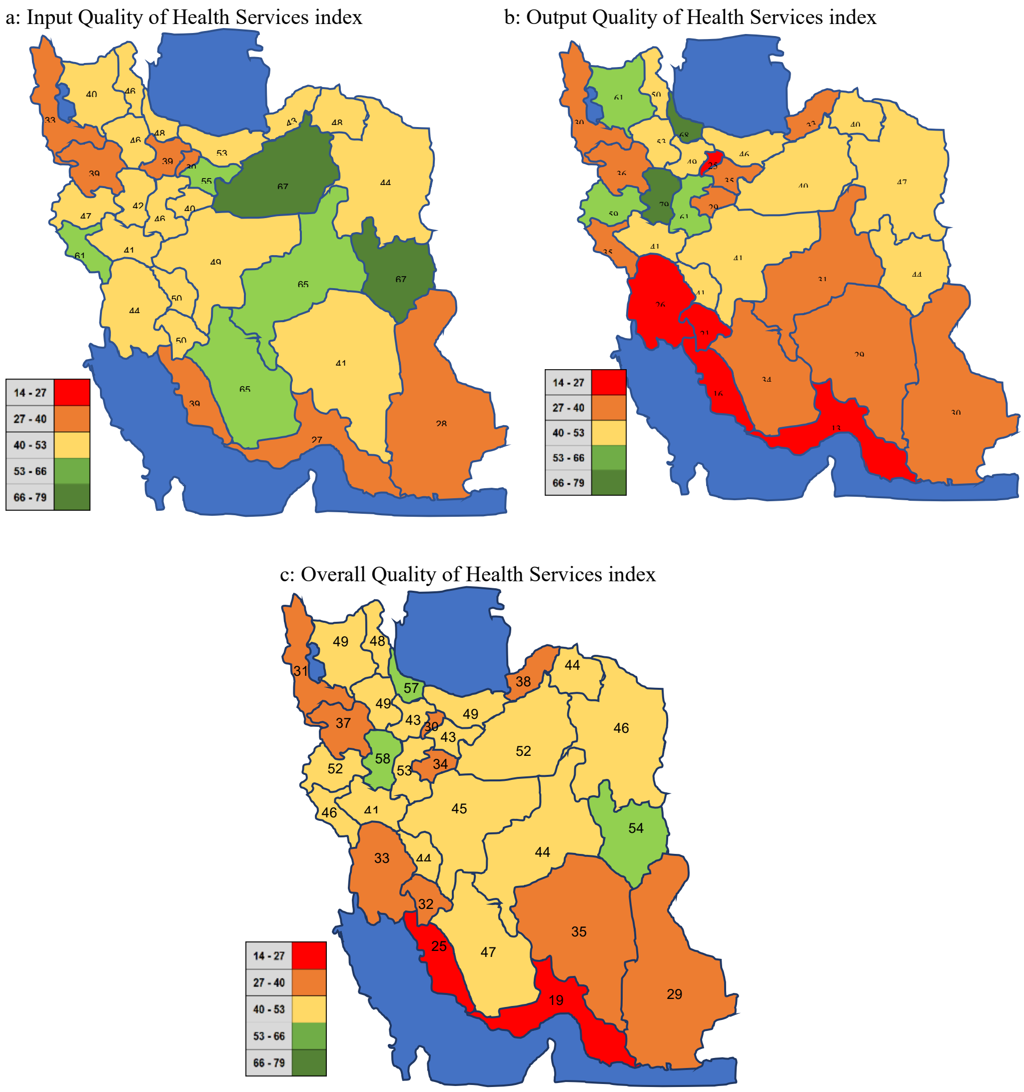

Figure 1. Iran's provincial Quality of Health Services index (average for 2011–2022): QHS_{INT}, QHS_{OUT}, and QHS_{OVE}
Source: Research calculations

exposure to ambient air pollution leads to an increase in the incidence of overall, cardiovascular, respiratory, and infectious hospitalizations (35). Chen et al also believe that even low levels of pollution can increase the burden on outpatient, inpatient, and emergency departments (36). Zhou et al estimated a cost-of-illness model in China between 1990 and 2021, and the results showed that air pollution imposes a heavy burden on health (37).

The direct and intra-regional coefficients of QHS_{INP} are 0.51 in the first model and 0.02 in the second model. These coefficients are statistically significant, indicating that an increase in QHS_{INP} will lead to an increase in QHS_{OVE} and QHS_{OUT} within the regions. QHS_{INP} is a highly significant variable and has the largest impact coefficient on OVE.

The direct and intra-regional impact of inflation (INF) is negative and significant in both models. This suggests that INF in Iranian provinces has led to a reduction in the quality of the health index. The impact coefficient for this variable is −0.03 in the first model and −0.01 in the second model. By reducing individuals' purchasing power, inflation makes healthcare services unaffordable, particularly for low-income populations. The increase in basic living costs due to inflation means that low-income households allocate a smaller portion of their income to health, consequently depriving themselves of essential services. Furthermore, inflation, by devaluing the national currency and increasing global costs, severely raises the prices of imported drugs and medical supplies. The pharmaceutical sector is particularly vulnerable, and increased costs can lead to shortages of essential medicines and an abundance of counterfeit or substandard drugs. Even domestic production of drugs and medical equipment faces challenges due to increased raw material and production costs, leading to higher final prices. The study by Rezaei et al confirms our findings. The prevalence of healthcare costs in Iran reduces households' ability to pay, to the extent that 7.9% of Iran's population has fallen into poverty due to medical services. The poor often have high treatment costs, while the rich have high healthcare costs (38).

Overall, INF significantly impacts QHS_{OVE} in Iran by reducing people's purchasing power, increasing the cost of drugs and medical equipment, pressuring healthcare centers, reducing motivation, leading to the migration of healthcare personnel, and imposing government budget constraints.

The indirect and intra-regional impact coefficients of inequality (*JC*) are −0.02 in the first model and −0.01 in the second model. These coefficients are statistically significant, indicating that an increase in inequality will lead to a decrease in QHS_{OVE} and QHS_{OUT} within the regions, which aligns with theoretical expectations. The study of Shaibani et al confirms our findings. Using a meta-analysis method to assess geographical health inequality, they examined factors such as the distribution of physicians and the relationship between poverty and mortality, and their results showed that these factors have a high correlation with health inequality (39). By examining network maps of the distribution of economic, social, and environmental infrastructures, Tu et al also showed that contrasting inequalities in access to infrastructure affect health outcomes (40).

The direct effect of education on the quality of health services is positive and statistically significant, with coefficients of 0.07 in the first model and 0.02 in the second. These findings align with research expectations, as education can positively influence health service quality through several channels. These include increasing public health awareness and personal hygiene practices, developing a specialized human capital in the healthcare sector, and boosting economic productivity. The spatial (spillover) effects of education mean that a rise in a province's educational level positively influences the quality of health services in neighboring provinces. This is attributed to geographical proximity and inter-provincial connections. In essence, new health-related knowledge and technologies are easily transferred from provinces with higher education levels to their neighbors. This transfer can occur through academic collaborations, conferences, or even the migration of specialists. Additionally, neighboring provinces may adopt the successful health policies and programs implemented in the more educated province. Ultimately, as a province improves its education and infrastructure, it may establish specialized health centers that serve both its own residents and those of nearby provinces. This is particularly evident in provinces like Tehran, Fars, or Yazd, which function as regional healthcare hubs. The study by Jia et al confirms our findings. Using spatial econometrics, they showed that increasing the level of public services in a particular province not only improves the health outcomes of its residents but also creates a spatial spillover effect, thereby positively impacting the health of residents in neighboring provinces (41).

Discussion

The findings indicate a negative correlation between the direct impact of carbon emissions, income inequality, and inflation, and the quality of health services. Conversely, the impact of provincial GDP, education, and the health input index on health service quality is positive. These results are in line with expectations from the research literature. Furthermore, the indirect effect of GDP on health service quality is negative and significant. This indirect negative relationship between GDP and the quality of healthcare service delivery can be analyzed through several lenses. These include, but are not limited to, population migration from poorer to wealthier provinces, competition for limited healthcare resources favoring wealthier provinces, environmental pollution spillover effects from richer to poorer provinces, and imbalances in policies and investments that may benefit higher-income regions.

Furthermore, the health output index data, such as infant mortality and mortality rates for each province, were obtained from the Ministry of Health. This data is based on deaths registered in hospitals within each province, without considering the place of residence of the individuals. For example, suppose an infant with an illness is taken to a medical hub province like Fars, Tehran, or Yazd for superior healthcare services and passes away. In that case, their death is recorded in the host province, not their home province. Therefore, this creates a negative spillover effect on neighboring provinces if a province experiences economic growth without a corresponding improvement in the quality of health services. For instance, provinces like Bushehr and Khuzestan have seen significant economic development and high incomes from the oil, gas, and petrochemical industries. However, health and medical services have not grown at the same pace, compelling residents to travel to neighboring provinces to access quality healthcare. It appears that the negative indirect effect of income on health service quality likely stems from a complex interplay of these economic, social, and environmental factors, where the prosperity of certain areas may inadvertently lead to poorer health outcomes in others.

Previous studies have mainly estimated the relationship between regression models without considering indirect effects. This study can help policymakers by considering the factors affecting the quality of health services in the provinces of Iran in terms of spatial effect for the first time, which.

Strengths and limitations of the study

To the best of our knowledge, no prior study has investigated the spatial effects of carbon emissions on the Quality of Health Services (QHS) index in Iran's provinces. This study examines the impact of carbon emissions, along with other control variables, on two indices: an output index and a composite index constructed using the entropy method. However, this study has specific limitations. Due to data constraints, the indices were constructed using only available information from 2011 to 2022. The input variables for the health sector include the number of physicians and nurses per capita, the number of hospital beds, the number of rehabilitation facilities, and the number of pharmacies. The output variables for the QHS index include the infant mortality rate (under 1 year), the proportion of the population over 65 years, and the number of registered deaths in a year. The findings from this research can be helpful for optimal resource allocation and regional policymaking. While other variables, such as patient satisfaction, access to health services, and treatment success rates, could have been included in the construction of the index, data were scarce for these variables across all provinces for the specified period. Finally, since this study exclusively used the entropy method for index construction, we recommend that future research utilize other indexing methods as well as dynamic estimation techniques to further validate and expand upon these findings.

Conclusion

The findings reveal a complex interplay among economic growth, environmental factors, health resources, and macroeconomic stability in shaping the quality of healthcare services within Iranian provinces. The results pertaining to GDP, particularly its contrasting direct and spatial effects, suggest that while provincial economic prosperity can yield direct health benefits, it may also generate negative externalities for neighboring regions. The negative impact of carbon emissions, inflation, and income inequality on "QHS_{OVE}" and "QHS_{OUT}" underscores the critical importance of environmental protection and macroeconomic management for public health. Finally, the vital role of QHS_{INP} in enhancing "QHS_{OVE}" and "QHS_{OUT}" is reaffirmed. This study's findings indicate that improving "QHS_{OVE}" and "QHS_{OUT}" necessitates a multifaceted approach, encompassing not only direct healthcare investments but also broader economic and environmental considerations. Therefore, it is recommended that policies be implemented to address regional disparities in healthcare access and quality through equitable resource allocation and investment across provinces. This could include targeted budget allocation for less developed regions and initiatives to attract and retain healthcare professionals in these areas. To mitigate carbon emissions and their detrimental effects on public health, stricter environmental regulations should be enforced, and sustainable development practices should be promoted. Macroeconomic stability should be prioritized, with measures taken to control inflation to ensure the affordability and accessibility of healthcare services and medications. Investment in health infrastructure, human resources, and the supply chain for essential medical goods should be continued and strengthened. Furthermore, policies should be considered that encourage wealthier provinces to reduce negative spillover effects on neighboring regions, such as joint environmental protection initiatives or resource-sharing mechanisms.

Given the direct relationship between education level and GDP growth, it is essential for investments to be targeted and for high-quality economic growth—meaning growth accompanied by reduced inequalities—to be achieved. Reducing inequalities in access to healthcare and medical services is a long-term prerequisite for increasing the quality of QHS. The study shows that carbon emissions, inflation, and inequality collectively reduce the quality of QHS. For this reason, comprehensive and integrated environmental, social, and economic policies must be considered. When facing these factors that diminish QHS quality, it is necessary to adopt a dynamic perspective on these issues, such that the feedback loops among these factors are taken into account and the necessary policies for improving QHS quality are implemented.

Acknowledgements
We are grateful to the Journal of Research in Health Sciences for considering our manuscript for review. We look forward to the possibility of contributing to the journal's esteemed publications.

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Competing interests
The authors confirm that they have no conflicts of interest to declare.

Ethical issues
There were no ethical issues in the preparation and writing of this article. The authors certify that this article has not been published previously and is not currently under consideration for publication elsewhere. All data and information presented in this article have been collected and analyzed transparently and in compliance with ethical research principles. This study did not require ethical approval, as it utilized secondary data that were already publicly available (ethical code: IR.BPUMS.REC.1404.065).

Funding
This study was self-funded by the authors and received no external financial support from any funding organization.

References
1. Jarraud M, Steiner A. Summary for policymakers. In: Climate Change 2013: The Physical Science Basis: Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press; 2012. p. 3-22. doi: 10.1017/cbo9781139177245.003.
2. Stiglitz JE. Making Globalization Work. New York: WW Norton & Company; 2006.
3. Standing G. The Corruption of Capitalism: Why Rentiers Thrive and Work Does Not Pay. London: Biteback Publishing; 2021. doi: 10.2139/ssrn.3768790
4. World Health Organization (WHO). Air Quality, Energy and Health. Geneva: WHO; 2025. doi: 10.2471/b09456
5. Lemons J. Atmospheric carbon dioxide. Environ Ethics. 1983;5(1):21-32. doi: 10.5840/enviroethics19835132.
6. Patz JA, Frumkin H, Holloway T, Vimont DJ, Haines A. Climate change: challenges and opportunities for global health. JAMA. 2014;312(15):1565-80. doi: 10.1001/jama.2014.13186
7. Folland S, Goodman AC, Stano M, Danagoulian S. The Economics of Health and Health Care. 9th ed. New York: Routledge; 2024. p. 1-740. doi: 10.4324/9781003308409
8. Hartwell H. Global public health workforce. Perspect Public Health. 2014;134(5):234. doi: 10.1177/1757913914545568
9. Evans GW. Environmental Stress. Cambridge: Cambridge University Press; 1984.
10. Chatterjee S, Sarkar K. Appraisal of urban–rural disparities in access to health care facilities and exposure to health risk factors: a case study of Durgapur industrial region, India. GeoJournal. 2022;87(5):4007-24. doi: 10.1007/s10708-021-10480-9
11. Or Z, Seppänen AV. The role of the health sector in tackling climate change: a narrative review. Health Policy. 2024;143:105053. doi: 10.1016/j.healthpol.2024.105053
12. Watts N, Amann M, Arnell N, Ayeb-Karlsson S, Belesova K, Boykoff M, et al. The 2019 report of the Lancet Countdown on health and climate change: ensuring that the health of a child born today is not defined by a changing climate. Lancet. 2019;394(10211):1836-78. doi: 10.1016/s0140-6736(19)32596-6
13. Doshi S, Vuppula S, Jaggi P. Healthcare sustainability to address climate change: call for action to the infectious diseases community. J Pediatric Infect Dis Soc. 2024;13(6):306-12. doi: 10.1093/jpids/piae029
14. Leal Filho W, Luetz JM, Thanekar UD, Dinis MA, Forrester M. Climate-friendly healthcare: reducing the impacts of the healthcare sector on the world's climate. Sustain Sci. 2024;19(3):1103-9. doi: 10.1007/s11625-024-01487-5
15. Morais L, Lopes A, Rocha J, Nogueira PJ. Beyond usual geographical scales of analysis: implications for healthcare management and urban planning. Port J Public Health. 2023;40(3):140-54. doi: 10.1159/000527162
16. Watts N, Amann M, Arnell N, Ayeb-Karlsson S, Belesova K, Berry H, et al. The 2018 report of the Lancet Countdown on health and climate change: shaping the health of nations for centuries to come. Lancet. 2018;392(10163):2479-514. doi: 10.1016/s0140-6736(18)32594-7
17. Ebi KL, Semenza JC. Community-based adaptation to the health impacts of climate change. Am J Prev Med. 2008;35(5):501-7. doi: 10.1016/j.amepre.2008.08.018
18. Cohen AJ, Brauer M, Burnett R, Anderson HR, Frostad J, Estep K, et al. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. Lancet. 2017;389(10082):1907-18. doi: 10.1016/

s0140-6736(17)30505-6
19. Lelieveld J, Evans JS, Fnais M, Giannadaki D, Pozzer A. The contribution of outdoor air pollution sources to premature mortality on a global scale. Nature. 2015;525(7569):367-71. doi: 10.1038/nature15371
20. Hosking J, Campbell-Lendrum D. How well does climate change and human health research match the demands of policymakers? A scoping review. Environ Health Perspect. 2012;120(8):1076-82. doi: 10.1289/ehp.1104093
21. Romanello M, McGushin A, Di Napoli C, Drummond P, Hughes N, Jamart L, et al. The 2021 report of the Lancet Countdown on health and climate change: code red for a healthy future. Lancet. 2021;398(10311):1619-62. doi: 10.1016/s0140-6736(21)01787-6
22. Saisana M. Composite indicators: a review. In: Proceedings of the Second Workshop on Composite Indicators of Country Performance. Paris: OECD; 2004.
23. Steurer J. The Delphi method: an efficient procedure to generate knowledge. Skeletal Radiol. 2011;40(8):959-61. doi: 10.1007/s00256-011-1145-z
24. Diakoulaki D, Mavrotas G, Papayannakis L. Determining objective weights in multiple criteria problems: the CRITIC method. Comput Oper Res. 1995;22(7):763-70. doi: 10.1016/0305-0548(94)00059-h
25. Pearson K. LIII. On lines and planes of closest fit to systems of points in space. Lond Edinb Dublin Philos Mag J Sci. 1901;2(11):559-72. doi: 10.1080/14786440109462720
26. Shannon CE, Weaver W. The mathematical theory of communication. Bell Syst Tech J. 1949;27(3):379-423. doi: 10.2307/3611062
27. Farahmandian V, Farahmandian M, Mehrabanfar E, Afkhami M. The role of information technology in contemporary health management in Iran in regard with a future outlook. Business Intelligence Management Studies. 2015;3(10):21-38.
28. Alotaibi YK, Federico F. The impact of health information technology on patient safety. Saudi Med J. 2017;38(12):1173-80. doi: 10.15537/smj.2017.12.20631
29. Motiei Langeroudi SH, Rezvani M, Faraji Sabokbar HA, Nemati M. Analysis of relative pattern between reacted social and economic districts by ICT in rural life case study: central part of Gorgan township. Urban-Regional Studies and Research (University of Isfahan). 2010;1(3):71-90.
30. Hosseinzadeh R. Indirect effect of household consumption on CO2 emission in Iran. Int J Environ Sci Technol. 2023;20(8):8571-8. doi: 10.1007/s13762-023-05040-2
31. Anselin L. Spatial econometrics. In: Handbook of Spatial Analysis in the Social Sciences. Cheltenham: Edward Elgar Publishing; 1999. p. 101-22. doi: 10.4337/9781789903942.00014
32. Nobahar E, Ghorbani F, Hadadmoghadam M. Investigating the relationship between unemployment and net immigration: a spatial econometric approach. J Econ Res Policies. 2021;29(98):135-76. doi: 10.52547/qjerp.29.98.135
33. Deaton A. Health, Inequality, and Economic Development. Journal of Economic Literature. 2003;41 (1):113–158. doi: 10.1257/002205103321544710
34. Qin A, Qin W, Hu F, Wang M, Yang H, Li L, et al. Does unequal economic development contribute to the inequitable distribution of healthcare resources? Evidence from China spanning 2001-2020. Global Health. 2024;20(1):20. doi: 10.1186/s12992-024-01025-z
35. Abed Al Ahad M, Demšar U, Sullivan F, Kulu H. Long term exposure to ambient air pollution and hospital admission burden in Scotland: 16-year prospective population cohort study. BMJ Open. 2024;14(12):e084032. doi: 10.1136/bmjopen-2024-084032
36. Chen F, Zhang W, Bani Mfarrej MF, Saleem MH, Ali Khan K, Ma J, et al. Breathing in danger: Understanding the multifaceted impact of air pollution on health impacts. Ecotoxicol Environ Saf. 2024;280:116532. doi: 10.1016/j.ecoenv.2024.116532
37. Zhou D, Yang Y, Zhao Z, Zhou K, Zhang D, Tang W, et al. Air pollution-related disease and economic burden in China, 1990-2050: a modelling study based on Global Burden of Disease. Environ Int. 2025;196:109300. doi: 10.1016/j.envint.2025.109300
38. Rezaei S, Karimi M, Soltani S, Barfar E, Mohammadi Gharehghani MA, Badakhshan A, et al. Household financial burden associated with out-of-pocket payments for healthcare in Iran: insights from a cross-sectional survey. BMC Health Serv Res. 2024;24(1):1062. doi: 10.1186/s12913-024-11477-z
39. Shaibani MJ, Fazaeli AA. Robust prediction of healthcare inflation rate with statistical and AI methods in Iran. J Appl Math. 2024;2024(1):1193134. doi: 10.1155/2024/1193134
40. Tu Y, Chen B, Liao C, Wu S, An J, Lin C, et al. Inequality in infrastructure access and its association with health disparities. Nat Hum Behav. 2025;9(8):1669-82. doi: 10.1038/s41562-025-02208-3
41. Jia W, Liu L, Wang Z, Peng G. Analysis of the impact of public services on residents' health: a spatial econometric analysis of Chinese provinces. Int J Public Health. 2023;68:1605938. doi: 10.3389/ijph.2023.1605938