STATISTICS, OPTIMIZATION AND INFORMATION COMPUTING
Stat., Optim. Inf. Comput., Vol. **15**, January 2026, pp 128–137.
Published online in International Academic Press (www.IAPress.org)

Assessing the Relationship between Global Health Spending and Carbon Emissions using a Gradient-boosting Algorithm

Abdelsamiea T. Abdelsamiea [1,*], Elsayed E. Elashkar [2], Mohammad A. Zayed [3,*], Mohamed F. Abd El-Aal [4]

[1]*Department of Economics, College of Business, Imam Mohammad Ibn Saud Islamic University (IMSIU), Saudi Arabia*
[2]*Department of Administrative and Financial Sciences, College of Applied Studies, King Saud University, Saudi Arabia*
[3]*Department of Mathematics and Statistics, College of Science, Imam Mohammad Ibn Saud Islamic University (IMSIU), Saudi Arabia*
[4]*Department of Economics, Faculty of Commerce, Arish University, North Sinai, Egypt*

Abstract This paper examines the relationship between global health spending and CO2 emissions, the population aged 65 and above, GDP per capita growth, and GDP growth, utilizing a gradient-boosting algorithm. The paper confirms that the population aged 65 and older significantly influences current health expenditures (at 93%), GDP per capita growth (at 3%), and GDP growth and CO2 emissions, each contributing 2%. Additionally, the paper demonstrates a strong positive relationship between current health expenditures, the population aged 65 and older, and CO2 emissions. Conversely, there is a negative relationship between current health expenditures and both GDP growth and GDP per capita growth. This suggests that the world is optimistic about the transition to clean energy, which could lead to a decline in diseases and potentially reallocate part of health spending to other economic areas.

Keywords CO2 emissions, Gradient-Boosting Algorithm, Global Health Spending, GDP per capita growth, GDP growth.

AMS 2010 subject classifications 62P20, 62J99

DOI: 10.19139/soic-2310-5070-2858

1. Introduction

The connection between economic growth, environmental sustainability, and health spending is crucial in current policy discussions. As countries strive to improve their healthcare systems and enhance the well-being of their citizens, healthcare costs are increasing globally. However, the environmental impacts of increasing healthcare expenses are often neglected. Given the pressing need to balance sustainability with economic expansion, this study employs the gradient boosting algorithm, a sophisticated machine-learning method renowned for its accuracy and reliability in making predictions, to explore the link between global health spending and carbon emissions.

Global health expenditures have risen steadily, fueled by an aging population, advances in medical technology, and increased demand for high-quality healthcare services [28]. Although higher spending on health typically leads to better healthcare outcomes, it also requires considerable resource use, which may unintentionally increase carbon emissions. For example, the healthcare industry's dependency on energy-intensive activities, including the production of pharmaceuticals, hospital operations, and medical equipment manufacturing, has been recognized as a significant factor in carbon footprints [21]. Nevertheless, the relationship between global health spending and

*Correspondence to: Abdelsamiea T. Abdelsamiea (Email: taboelenien@imamu.edu.sa). Department of Economics, College of Business, Imam Mohammad Ibn Saud Islamic University (IMSIU), Saudi Arabia.,
Mohammad A. Zayed (Email: maazayed@imamu.edu.sa). Department of Mathematics and Statistics, College of Science, Imam Mohammad Ibn Saud Islamic University (IMSIU), Saudi Arabia.

ISSN 2310-5070 (online) ISSN 2311-004X (print)

carbon dioxide (CO_2) emissions is still not fully understood.
Economic growth is vital in shaping this relationship, often assessed through per capita and total GDP growth. Studies indicate that as economies expand, healthcare spending rises since nations invest more in improving public health systems [8]. Nevertheless, economic growth can lead to heightened industrial activity, increased energy use, and more significant emissions of greenhouse gases, which raises questions about its environmental viability [26]. Furthermore, demographic changes, especially the rising number of older individuals (65+), considerably influence healthcare expenditure patterns. Aging populations require more comprehensive healthcare services, resulting in higher spending levels and potentially increased emissions due to greater demand for medical resources [22].
A key element of this study involves excluding land use, land-use change, and forestry (LULUCF) emissions to concentrate on the industrial and economic factors impacting CO_2 emissions. Focusing on CO_2 emissions without LULUCF, this research seeks deeper insights into the interaction between healthcare expenditure, economic growth, and environmental factors. The growing elderly population profoundly affects healthcare systems; nations with more seniors typically experience heightened healthcare needs. This surge in demand subsequently impacts government expenditures and emission levels. Analyzing these elements allows us to understand the connection between healthcare funding, demographic changes, and environmental consequences.
This research is necessary because it can shape policy decisions on sustainable healthcare financing. Recognizing these links is essential for governments and organizations aiming to cut carbon emissions while providing sufficient healthcare services. By utilizing machine learning methods like gradient boosting, this study clarifies the connections among these elements and provides predictive insights to inform future policy-making. The findings from this research contribute to developing strategies that integrate economic growth, healthcare advancement, and environmental sustainability, fostering a comprehensive approach to global health.

2. Related works

Numerous studies have investigated the link between healthcare spending and carbon emissions, revealing various insights into how higher investments in health services influence the environment. Yin et al. [29] and Pichler et al. [21] identified that the healthcare industry accounts for roughly 5% of total national CO_2 emissions in OECD nations, China, and India. Their findings emphasize the significant role of hospitals, pharmaceuticals, and medical supply chains in contributing to greenhouse gas emissions. In addition, Akbar et al. [3] demonstrated a reciprocal causal relationship between healthcare spending, CO_2 emissions, and the human development index (HDI) in OECD countries, indicating the environmental costs linked to advancements in healthcare.
National healthcare system studies support these findings. According to Ganatra et al.[13] analysis, 8.5% of greenhouse gas emissions are attributable to the U.S. healthcare system. In a related study, Eckelman et al. [11] assessed Canada's healthcare system and calculated its annual emissions of around 33 million metric tons of CO_2. Their results highlight the urgent need for policy measures to reduce the carbon footprint of healthcare infrastructure.
Economic growth and energy consumption significantly impact this connection. Huang [14] and Socol et al. [25] revealed that CO_2 emissions negatively affect public health in the short term, while economic growth and more significant investments in healthcare can mitigate these effects over time. Pervaiz et al. [20] showed that hospital electricity consumption contributes to carbon emissions, yet utilizing renewable energy sources can mitigate environmental harm. Additionally, Wang et al. [27] and Moosa et al. [19] backed this notion by revealing a link between economic growth, increasing healthcare costs, and elevated emissions.
Numerous studies indicate significant regional differences in healthcare emissions. Atuahene et al. [6] examined CO_2 emissions linked to healthcare in China and India, finding that rapid industrial growth has intensified the environmental impact of healthcare services. Dritsaki et al. [9] analyzed the G7 countries in a parallel study, revealing a persistent long-term relationship between healthcare investment and CO_2 emissions. This suggests that wealthier nations tend to spend more on healthcare, resulting in higher per capita emissions.
Mitigation strategies, including carbon pricing and the adoption of renewable energy, have been extensively examined in various studies. Research by Apergis and Ben Jebli [5] and Huang et al. [15] indicated that carbon

pricing significantly reduces PM2.5-related mortality in low-income nations by cutting fossil fuel consumption. Similarly, studies by Kutlu & Örün [17] and Çobanoğulları [7] illustrated the link between economic development, increasing CO2 emissions, and escalating healthcare expenses, highlighting the need for sustainable policy solutions. The 2022 report "Pricing Carbon Emissions" examined the role of carbon pricing in mitigating health disparities linked to air pollution, highlighting its importance as a policy instrument.

Numerous studies highlight effective strategies for reducing carbon emissions in healthcare. Richie [23] stressed the crucial role of regulatory reforms in advancing sustainability within the US healthcare sector. Marchi et al. [18] devised a strategy for decarbonizing healthcare services by employing enhanced supply chain optimization and energy management. The financial consequences of pollution for healthcare systems were highlighted by Sasana et al. [24], who demonstrated that CO2 emissions significantly influenced government health spending in Indonesia. Dritsaki et al. [10] established a strong link between greenhouse gas emissions and healthcare costs in EU countries, urging the adoption of environmentally friendly policies in the sector.

Further studies have employed sophisticated methods to investigate these interactions. Abd El-Aal [1] utilized AI models to forecast the macroeconomic factors influencing CO2 emissions and healthcare expenses. Kumar [16] created hybrid machine-learning approaches to evaluate how emissions impact healthcare spending. Amiri et al. [4] analyzed these dynamics in MENA countries, identifying the interdependence of economic growth, healthcare investments, and CO2 emissions. Lastly, Abu Samah et al. [2] assessed the impact of the COVID-19 pandemic on healthcare-related emissions, highlighting the necessity for resilient and environmentally sustainable health systems.

Although extensive research has been conducted, essential gaps exist in understanding the link between healthcare spending and carbon emissions. While numerous studies utilize conventional econometric methods, advanced machine learning techniques like gradient boosting may uncover more profound insights into nonlinear relationships. Moreover, prior research often overlooks the impact of an aging population on healthcare-related carbon emissions, focusing primarily on economic growth and renewable energy. This study aims to deliver a comprehensive global analysis of the connections between healthcare spending, economic development, and environmental sustainability, contrasting with the current emphasis on specific countries or regions.

3. Data

The World Bank dataset used in this analysis includes annual data on global health spending and relevant economic and environmental variables. The dataset, which spans multiple nations from 2000 to 2022, highlights three crucial factors:

- Current Health Expenditure (% of GDP): This indicator represents total health expenditures as a percentage of GDP and serves as the dependent variable in our analysis.• Carbon Dioxide (CO2) Emissions (total) excluding LULUCF (Mt CO2e): This measure quantifies total CO2 emissions, excluding those from land use, land-use change, and forestry, serving as a crucial independent factor in the study.
- Annual GDP per Capita Growth (%): The yearly growth rate of GDP per capita highlights individual economic advancement.
- Annual GDP Growth (%): This measure reflects the yearly percentage rise in total GDP, offering a broader perspective on economic activity.
- Population Aged 65 and Older (% of Total Population): This statistic highlights the percentage of individuals aged 65 and older, a crucial demographic factor affecting healthcare demand.

These factors were chosen as they are relevant to the study's goals, enabling a thorough examination of the influence of environmental changes and economic growth on healthcare expenditures. The dataset has undergone preprocessing to manage missing values, normalize distributions, and improve feature selection for machine learning modeling; Table 1 and Figure 1 show that.

The table aims to provide a preliminary overview of the sample's characteristics.The values (mean, standard deviation, minimum, and maximum) demonstrate significant variation across countries in terms of development level and emissions, justifying the use of a non-linear model such as Gradient Boosting to interpret complex

Table 1. Feature Statistics

Variables*	Mean	Mode	Median	Dispersion	Minimum	Maximum
Current Health Expenditure (% of GDP)	9.52	8.62	9.42	0.048	8.62	10.86
CO2 emissions	33177.8	25725.4	34531.6	0.122	25725.4	38121
GDP Growth	2.97	-2.87	3.13	0.63	-2.87	6.35
GDP per Capita Growth	1.74	-3.85	1.90	1.08	-3.85	5.47
Population Aged 65 and Older (%of Total Population)	7.88	6.83	7.61	0.10	6.83	9.52

* Source of data: World Bank

relationships. The high variance in CO2 emissions and GDP per capita indicates structural differences between developed and developing countries. The proportion of the population 65+ exhibits variations that reflect different demographic structures and the impact of aging on health spending.

From the previous figures, it is clear that figure 1(A) shows a symmetrical and almost normal distribution around the median (9.42%). Figure 1(B) shows a slightly skewed distribution towards higher values, with the median (34,531) being higher than the mean. Figure 1(C) shows a strongly right-skewed distribution, with most of the data clustered around 1.5% to 1.9%, but there is a long ”tail” of countries with very high growth (up to 6%). Figure 1(D) shows a similar distribution for per capita income growth but is less extreme. There are still countries with negative growth, but positive growth is prevalent. Finally, figure 1(E) has a roughly symmetrical and normal distribution, indicating that this ratio follows a demographic pattern expected in many countries.

4. Methodology

This study utilizes the Gradient Boosting Algorithm (GB) as its primary modeling approach to explore the nonlinear and complex relationships between global health spending and carbon emissions. Gradient Boosting is a robust ensemble learning technique that builds a sequence of weak predictive models, typically decision trees, and enhances them iteratively to reduce prediction error.

4.1. Mathematical Formulation

Given a dataset $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{n}$ where,

- (x_i)represents the inputs (GDP growth, population aging, GDP per Capita Growth, and CO2 emissions)
- (y_i) denotes the target variable (global health spending)

Gradient Boosting builds a predictive model in an additive manner [12]:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x),$$

Where:

- $F_m(x)$ is the improved model at iteration
- $F_{m-1}(x)$ is the previous model
- γ_m the learning rate that controls the step size
- h_m is the new weak learner (typically a decision tree) fitted to the residual errors

The residual errors are calculated as:

$$r_{\underline{im}} = -\frac{\partial L(y_i, F(x_i))}{\partial F(x_{\underline{i}})}$$

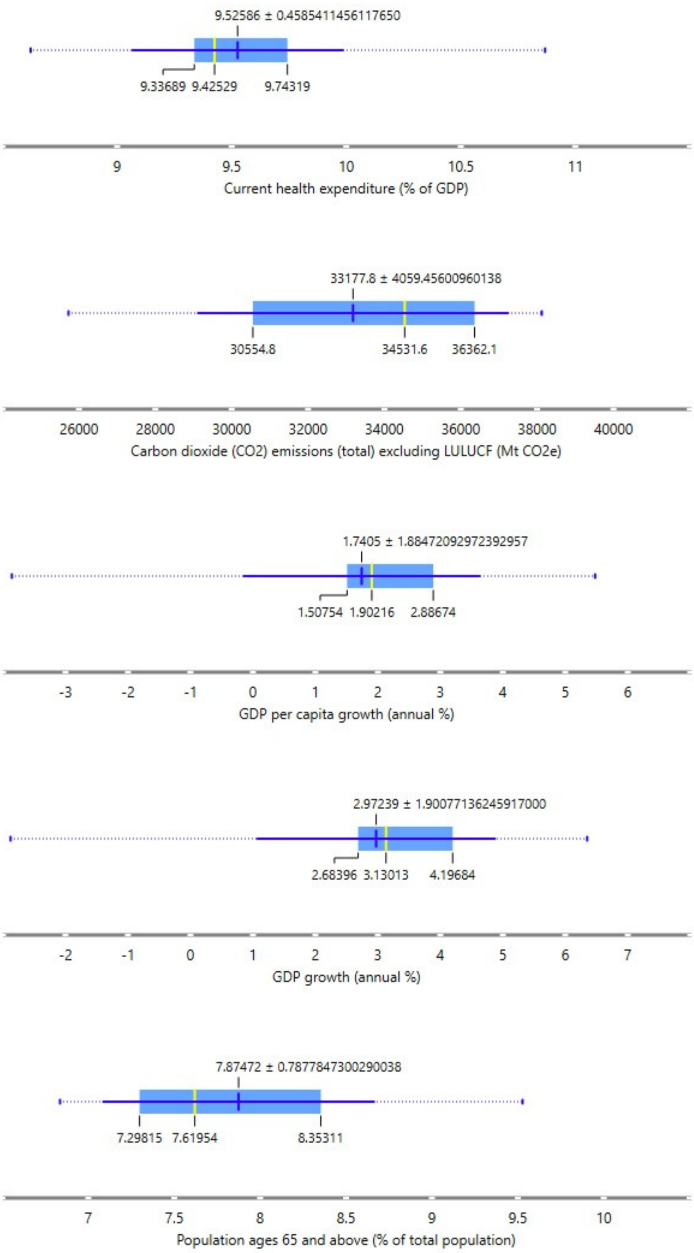

Figure 1. Score for each variable in a box plot

Where:

- $L(y_i, F(x_i))$ is the loss function, such as Mean Squared Error (MSE), which measures the difference between actual and predicted values,
- r_{im} symbolizes the pseudo-residuals that aid in model refinement.

Table 2. Feature importance

Variables	Scores (%)
Population Aged 65 and above (%of Total Population)	93
GDP per Capita Growth	3
GDP Growth	2
CO2 emissions	2

4.2. *Optimized Gradient Boosting Approach*

By modifying hyper-parameters like these, this study uses an optimized form of gradient boosting to increase forecast accuracy and avoid over-fitting.

- Number of Trees (M): The total number of boosting iterations.
- Learning Rate (γ): a shrinkage parameter that regulates each tree's contribution.
- Max Depth (d): establishes each decision tree's maximum depth.
- Subsampling Rate (ρ): specifies the percentage of training samples utilized for each boosting iteration.

The optimization function that was employed in this study is described as follows [12]:

$$\min_{\Theta} \sum_{i=1}^{n} L(y_i, F_M(x_i, \Theta)) + \lambda \|\Theta\|^2,$$

Where:

- θ symbolizes the group of parameters undergoing optimization,
- λ is a regularization coefficient to avoid over-fitting and manage model complexity.

4.3. *Feature Importance Analysis*

SHAP values are calculated to analyze the model's outputs and comprehend the relative importance of each predictor variable, as shown in Table 2. The importance of a feature is x_i quantified as (Friedman, 2001):

$$\phi_j = \sum_{S \subseteq X \setminus \{j\}} \frac{|S|!(|X| - |S| - 1)!}{|X|!} [F(S \cup \{j\}) - F(S)],$$

Where:

- ϕ_j is the Shapley value indicating the contribution of feature x_j to model predictions,
- X represents a subset of all features excluding j,
- $F(S)$ and $F\left(S \cup \{j\}\right)$ denote the model's prediction with and without feature x_j.

Table 2 shows that the Population Aged 65 and above is the higher influencer on current health expenditures by 93%, GDP per capita growth by 3%, and GDP growth and CO2 emissions by equal contribution of 2%.

4.4. *Model Evaluation Metrics*

Many error measurements are used to evaluate the effectiveness of GB regression, as shown in Table 3:
Mean Squared Error (MSE):

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{MSE}$$

Table 3. Accuracy comparison between algorithms

Algorithms	**MSE**	**RMSE**	**MAE**	R^2
GB	0.103	0.321	0.211	0.508
RF	0.142	0.377	0.288	0.322
DT	0.176	0.420	0.286	0.162

Table 4. Pearson correlations

Independent Variables*	**Correlation coefficient**
Population Aged 65 and Older (%of Total Population)	0.824
CO2 emissions	0.616
GDP Growth	-0.428
GDP per Capita Growth	-0.373

* Dependent variable: Current Health Expenditure (% of GDP)

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

R-squared (R^2):

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

Table 3 shows that the gradient boosting algorithm is more accurate than the RF and DT algorithms. The GB has a higher R2 value and the lowest MSE value, so the paper depends on it.

5. Relationships analysis

In this section, the relationships between variables in the model are analyzed using Pearson correlation coefficient (Table 4, Figure 2) and partial dependence plots (PDPs) (Figure 3). This gives an indication of both the existing relationships and the trend of future predictions based on the algorithm's regression coefficients.

Table 4 shows a strong positive relationship between current health expenditures and both variables: the Population Aged 65 and older and CO2 emissions. On the other hand, there is a negative relationship between current health expenditures and both variables, GDP Growth and GDP per Capita Growth. Figure 2 shows these relations:

Figure 2 shows:

- Older populations and health spending: A higher proportion of older people is strongly and directly associated with increased health spending.
- Carbon emissions and health spending: Countries with higher emissions tend to spend larger proportions of their economies on health.
- Economic growth and health spending: Accelerating economic growth is associated with a decline in the relative share of health spending in GDP.
- Per capita income growth and health spending: An improvement in per capita income does not necessarily lead to a larger share of the economy being allocated to the health sector

In more detail, partial dependence plots (PDPs) can be used to illustrate the relationship between the dependent and independent variables, as illustrated in Figure 3.

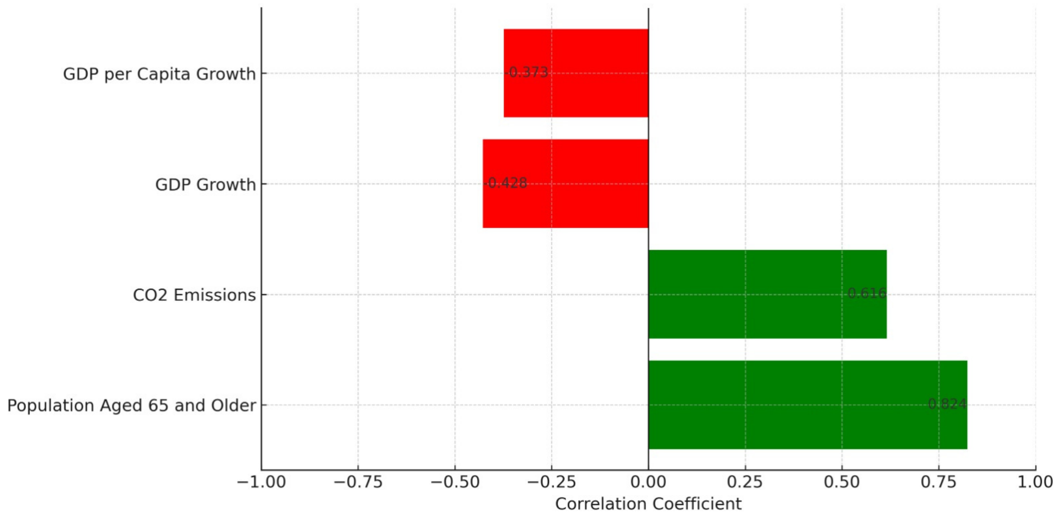

Figure 2. Pearson correlations graph

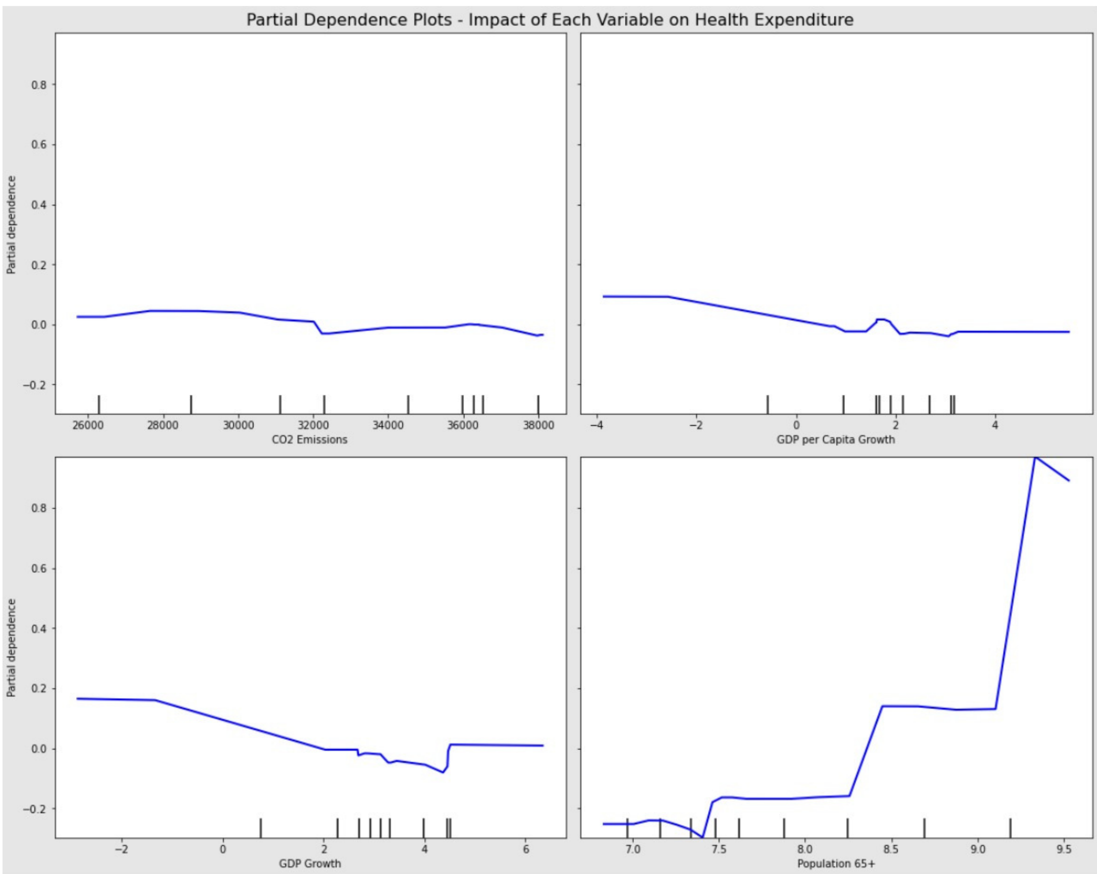

Figure 3. Partial Dependence plots- impact of each variable on health expenditure

The PDPs relied on complex relationships between perspectives and influencing factors, noting that current data shows a near-linear increase in spending. Non-linearity and particular turning points in the relationship between explanatory variables and public spending highlight the importance of demographic planning, consideration of health costs in industrial development policies, and the need to maintain resource allocation to the public sector despite economic changes.

6. Conclusion

Another important aspect is how technological advancements and policy interventions influence the connection between healthcare spending and carbon emissions. Medical technology innovations, digital health solutions, and eco-friendly healthcare infrastructure can lessen the environmental impact of the healthcare sector while enhancing service efficiency. Furthermore, government initiatives promoting sustainable healthcare practices—including carbon taxes, incentives for environmentally friendly hospitals, and stricter environmental regulations—can significantly decrease the sector's carbon footprint. Future research should analyze how these technological and policy changes affect the long-term viability of healthcare financing and environmental stewardship.
Utilizing the Gradient Boosting Algorithm, this study offers valuable insights into the connection between global health spending and carbon emissions. The findings emphasize that the aging population (65 years and older) is the most significant factor in healthcare expenditures, making up nearly 93% of the variations. Furthermore, CO2 emissions demonstrate a positive correlation with health expenditures. Meanwhile, GDP growth and GDP per capita growth display a negative relationship, suggesting that economic expansion may lead to a decreased proportion of healthcare spending relative to GDP.
Gradient Boosting significantly identifies nonlinear relationships, surpassing conventional models like Decision Trees and Random Forests. This highlights the essential role of advanced predictive methods in shaping economic and environmental policies. However, challenges persist, such as excluding LULUCF emissions and potential variations in regional healthcare regulations. Future research should concentrate on models tailored for individual countries and evaluate the long-term impacts of carbon pricing and the adoption of renewable energy on healthcare costs.
Planning for healthcare must consider economic and environmental factors. Legislators must balance reducing the healthcare sector's environmental impact with meeting the growing demand for healthcare. Focusing on sustainable healthcare finance and supporting green technologies can all help balance public health, ecological integrity, and economic growth.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

1. M. F. Abd El-Aal, *The relationship between CO2 emissions and macroeconomics indicators in low and high-income countries: using artificial intelligence*, Environment, Development and Sustainability, 2024.
2. I. H. Abu Samah, I. M. Abd Rashid, W. Husain, S. Ibrahim, H. Hamzah, and M. H. Amlus, *The impact of healthcare expenditure and healthcare sector growth on CO2 emission using dynamic panel data system GMM estimation model during COVID-19 crisis*, International Journal of Energy Economics and Policy, vol. 10(6), 235–241, 2020.
3. M. Akbar, A. Hussain, A. Akbar, and I. Ullah, *The dynamic association between healthcare spending, CO2 emissions, and human development index in OECD countries: evidence from panel VAR model*, Environment, Development and Sustainability, vol. 23(7), 10470–10489, 2021.
4. F. Amiri, Z. Tabatabaei-Nasab, and M. A. Dehqantafti, *Causal Simultaneous Relation Between Economic Growth, Health Expenditure, and CO2 Emissions in MENA Countries*, The Journal of Tolooebehdasht, vol. 17(7), 2019.
5. N. Apergis and M. Ben Jebli, *Does Renewable Energy Consumption and Health Expenditure Decrease Carbon Dioxide Emissions? Evidence for sub-Saharan African countries*, Research Papers in Economics, 2015.

6. S. A. Atuahene, K. Yusheng, and G. Bentum-Micah, *Health Expenditure, CO2 Emissions, and Economic Growth: China vs. India*, Preprints, 2020.
7. G. Çobanoğulları, *Exploring the link between CO2 emissions, health expenditure, and economic growth in Türkiye: evidence from the ARDL model*, Environment, Development and Sustainability, 2024.
8. J. L. Dieleman, R. Baral, M. Birger, A. L. Bui, A. Bulchis, A. Chapin, and C. J. Murray, *US spending on personal health care and public health, 1996-2013*, Jama, vol. 316(24), 2627-2646, 2016.
9. M. Dritsaki and C. Dritsaki, *The Relationship Between Health Expenditure, CO2 Emissions, and Economic Growth in G7: Evidence from Heterogeneous Panel Data*, Journal of The Knowledge Economy, 1–26, 2023.
10. M. Dritsaki, C. Dritsaki, V. Argyriou, and P. Sarigiannidis, *The impact of greenhouse gas emissions and economic growth on health expenditure of EU countries: A panel data analysis*, Journal of Infrastructure, Policy and Development, vol. 8(6), 4462, 2024.
11. M. J. Eckelman, J. D. Sherman, and A. J. MacNeill, *Life cycle environmental emissions and health damages from the Canadian healthcare system: An economic-environmental-epidemiological analysis*, PLOS Medicine, vol. 15(7), e1002623, 2018.
12. Friedman, J. H., *Greedy function approximation: a gradient boosting machine*, Annals of statistics, 1189-1232, 2001.
13. S. Ganatra, S. S. Dani, S. G. Al-Kindi, and S. Rajagopalan, *Health Care and Climate Change: Challenges and Pathways to Sustainable Health Care*, Annals of Internal Medicine, vol. 175, 1598–1600, 2022.
14. C. Huang, *Exploring the interrelationship among health status, CO2 emissions, and energy use in the top 20 highest emitting economies based on the CS-DL and CS-ARDL approaches*, Environmental Science and Pollution Research, 2023.
15. X. Huang, V. Srikrishnan, J. Lamontagne, K. Keller, and W. Peng, *Pricing carbon emissions reduces health inequities from air pollution exposure*, Authorea Preprints, 2022.
16. S. Kumar, *A novel hybrid machine learning model for prediction of CO2 using socio-economic and energy attributes for climate change monitoring and mitigation policies*, Ecological Informatics, vol. 79, 102253, 2023.
17. G. Kutlu and E. Örün, *The effect of carbon dioxide emission, GDP per capita and urban population on health expenditure in OECD countries: a panel ARDL approach*, International Journal of Environmental Health Research, 1–10, 2022.
18. C. Marchi, W. Cristiano, B. Armocida, M. Martuzzi, and L. Mancini, *Decarbonizing healthcare sector: from a review to a framework of practical solutions*, European Journal of Public Health, vol. 33(Supplement 2), 2023.
19. N. Moosa, V. Ramiah, and V. Pereira, *A plausible explanation for the negative correlation between environmental degradation and healthcare expenditure*, Applied Economics Letters, vol. 28(16), 1377–1381, 2021.
20. R. Pervaiz, F. Faisal, S. U. Rahman, R. Chander, and A. Ali, *Do health expenditure and human development index matter in the carbon emission function for ensuring sustainable development? Evidence from the heterogeneous panel*, Air Quality, Atmosphere & Health, vol. 14(11), 1–12, 2021.
21. P.-P. Pichler, I. S. Jaccard, U. Weisz, and H. Weisz, *International comparison of health care carbon footprints*, Environmental Research Letters, vol. 14(6), 064004, 2019.
22. B. Rechel, Y. Doyle, E. Grundy, and M. McKee, *How can health systems respond to population ageing?*, World Health Organization, 2009.
23. C. Richie, *Can United States Healthcare Become Environmentally Sustainable? Towards Green Healthcare Reform*, Journal of Law Medicine & Ethics, vol. 48(4), 643–652, 2020.
24. H. Sasana, P. Kusuma, and Y. Setyaningsih, *The Impact of CO2 Gas Emissions on Government Expenditure of Health Sector in Indonesia*, E3S Web of Conferences, vol. 125, 04004, 2019.
25. A. Socol, H. Iuga, D. Socol, and I. Iuga, *Does climate change drive up government healthcare costs in the European Union?*, Frontiers in Environmental Science, vol. 11, 1286099, 2023.
26. D. I. Stern, *The rise and fall of the environmental Kuznets curve*, World development, vol. 32(8), 1419-1439, 2004.
27. Z. Wang, M. M. Asghar, S. A. H. Zaidi, S. A. H. Zaidi, and B. Wang, *Dynamic linkages among CO 2 emissions, health expenditures, and economic growth: empirical evidence from Pakistan*, Environmental Science and Pollution Research, vol. 26(15), 15285–15299, 2019.
28. K. A. Xu, A. Soucat, J. Kutzin, C. Brindley, N. V. Maele, H. Touré, and A. Siroka, *Public spending on health: a closer look at global trends*, World Health Organization, Geneva, 10, 2018.
29. H. Yin, B. Sharma, H. Hu, F. Liu, M. Kaur, G. Cohen, R. McConnell, and S. P. Eckel, *Predicting the climate impact of healthcare facilities using gradient boosting machine*, Cleaner Environmental Systems, vol. 11, 100155, 2023.