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Global evidence of environmental and lifestyle effects on medical expenditures across 154 countries

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ABSTRACT

Increases of health care expenditures (HCEs) challenge the financial capacity of governments and bring into question the quality of health care services in each country. It is known that modifiable risk factors (e.g. alcohol consumption) and certain environmental variables allow HCEs to be modeled without impairing the quality of healthcare services. We provide a worldwide statistical analysis of how HCEs can be reduced and with what statistical power/probability. The design was retrospective and was based on linear and nonlinear multiple regression models. The HCEs, alcohol consumption, renewable energy consumption, suicide rate, economic reversal of the environmental damage caused by CO_2 emissions (ERCDE) and sales-focused jobs (SJs) were measured. The type of government and the most searched Twitter worldwide topics were also analyzed. A total of 154 countries (n) participated. Reducing alcohol consumption, SJs and ERCDE predicts linear reductions of 33.1% of HCEs. Annual alcohol consumption between 4 and 5 L per person was found to have no negative impact on HCEs. Beyond this tipping point, alcohol consumption did predict significant increases in HCEs. It was also found that renewable energy consumption exponentially explained 35.2% of the reductions in HCEs. HCEs can be reduced in each country by controlling the consumption of renewable energies, the ERCDE, and the SJs. Specifically, by controlling alcohol consumption, SJs, and ERCDE the economic reduction in HCEs could be reduced annually by as much as $228.466 per person. We offer tipping points that governments can use to make effective health policy decisions that include *sustainable development goals*.

1. Introduction

The health care expenditure (also called HCE) invested in citizens is a crucial indicator for political and medical decision-making (Meskarpour Amiri et al., 2021; Radmehr and Adebayo, 2022). Numerous studies indicate that health care expenditure is related to people's lifestyle (Leigh et al., 2005; Ahmed et al., 2020). On one hand, lifestyles that promote healthy habits and behaviors would contribute to lower levels of health care expenditure (Vagnoni et al., 2018). On the other hand, unhealthy lifestyles would lead to a worsening of people's health and, consequently, increase health care expenditures (Biener and Decker, 2018). For example, epidemiological studies and systematic reviews found that 15 % of health care expenditure could be attributed to smoking (Ekpu and Brown, 2015), 11 % to alcohol consumption (Bouchery et al., 2011) and 9 % to obesity (Finkelstein et al., 2003; Fujita et al., 2018). Similarly, lifestyles that contribute positively to the reduction of health care expenditure can also be highlighted: the practice of physical exercise reduces it by between 1.5 % and 20.6 %[1] (Wang et al., 2004; Mori et al., 2011), vegetarian diets by 15 % (Lin et al., 2019) and low-sugar food intake by 4.7 % (Mekonnen et al., 2013). These types of habits or lifestyles are called modifiable risk factors (for variables that worsen HCE by increasing it) and health prevention factors (for variables that improve HCE by reducing it) (Lin, 2008). In this research we will focus on risk factors, their association with environmental factors and how these variables allow the modeling of health care expenditures on a global scale.

According to global data published in 2022 by the World Health Organization (WHO) (World Health Organization, 2022), health care expenditure has continued to increase over the last 10 years. However, these increases are not explained by modifiable risk factors alone (Deb

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[1] The rate was calculated from the data provided in Mori's research [12]. The following estimate of the reduction in yen was used:

$$\Delta Rate = \left(\frac{f_{CG}^{Max} - f_{EG}^{Max}}{f_{CG}^{Max}}\right)\cdot 100 = \left(\frac{395.133 - 313.744}{395.133}\right)\cdot 100 = 0.206\cdot 100 = 20.6$$

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and Norton, 2018); other studies have asked which environmental and ecological variables could affect increases in health care expenditure (Chen and Chen, 2021). Several independent studies have found that this increase is correlated with increases in industrial production and economic growth (measured in sales) in developed countries (Blanco-Moreno et al., 2013; Bilgili et al., 2021; Li et al., 2020). At the same time, it is unavoidable to note that industrial production is highly correlated with carbon dioxide emissions and the use of fossil fuel-based energy (Schröder and Storm, 2020). It is scientifically proven that pollution from carbon dioxide emissions and fossil fuel consumption have a negative impact on people's health (Yang and Liu, 2018; Apergis et al., 2018) and this impact feeds back positively into increases in health care expenditure (Yang et al., 2021). Fig. 1 shows the feedback loop or cycle that the environmental theoretical model proposes to explain increases in health care expenditure.

The feedback loop in Fig. 1 involves multiple complementary economic variables in addition to environmental indicators and modifiable risk factors. These other complementary variables are also important to better understand the context of how this feedback unfolds. One essential element that we must highlight is the *globalization* and internationalization of markets (Yang et al., 2021; Fervers et al., 2015). In this case, globalization refers to a process of integral transformation (i.e., social, political, technological and economic), which generates unilateral relations of dependence between countries, markets and organizations (Jani et al., 2019). Consequences of these interdependent relationships associated with globalization are the spread of diseases that were originally endemic, pandemics, industrial relocation, medical tourism and drug trafficking (including tobacco and alcohol) (Carrera and Bridges, 2006). These consequences are within the scope of modifiable risk factors (as they alter the local lifestyles or cultures of each country) and impact international economic evolution (Jakovljevic et al., 2021). Therefore, health care expenditures will not be independent of the effects of globalization, which will condition the interpretation of Fig. 1 and make it a complex theoretical approach.

Globalization also has a direct impact on environmental variables related to health care expenditures (Leigh et al., 2005). This has encouraged scientific discussion on how to assess the negative effects of environmental variables on people's health and on health care expenditure. For example, current studies found that environmental pollution explains 8 % of the increases in health care expenditure (Liu and Ao, 2021). The same is true for carbon dioxide emissions, which predicted expenditures between 2.04 % and 5 % (Gündüz, 2020; Lenzen et al., 2020). However, other studies that attempted to replicate these rates concluded that there was indeed an increase in health care expenditures, but these increases were not proportional to the actual health problems characterizing the population and justifying the medical expenditure invested (Shen et al., 2021). This mismatch could be explained by the fact that both pollution and the carbon footprint were evaluated exclusively as environmental and medical consequences; in other words, they analyzed the effects of pollution on air quality, medical diseases resulting from carbon dioxide emissions, and their economic impacts on health care expenditures (Sahoo and Sethi, 2021), but did not include economic reversal of the environmental damage caused by carbon dioxide emissions (hereafter referred to as ERCDE) produced by the pollution itself (Reis et al., 2022). The ERCDE is a hypothetical estimate that measures economically how much each government would have to spend on the environment if it wished to repair the damage caused by CO_2 emissions. These economic losses are correlated to health care expenditures because they represent damages or consequences produced by the pollution derived from CO_2 emissions. Following this logic, the ERCDE may interfere in the relationship between environmental variables and health care expenditures – the problem is that no evidence was

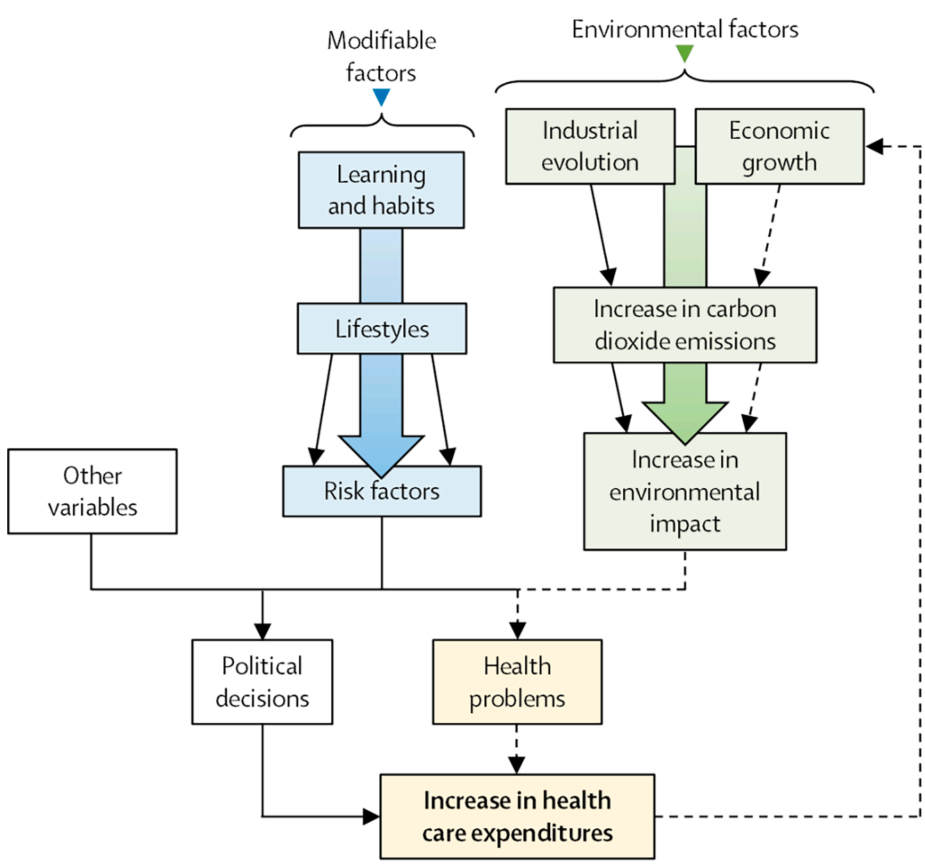

Fig. 1. Theoretical positive feedback environmental model that predicts systematic increases in health care expenditure. Dashed lines represent positive feedback. Diagram elaborated and designed by Prof. Álex Escolà-Gascón as a summary of the theoretical framework.

found to inform about the effects of the ERCDE on health care expenditures.

Environmental variables, gas emissions and pollution are related to the lifestyle of the population (Zhang et al., 2020). This means that the interaction between environmental variables and modifiable risk factors could also have direct consequences on health care expenditures. In fact, the implementation of environmentally sustainable lifestyles, the ecological regulation of the consumption of goods and services, recycling, and the use of renewable energies represent variables that are related to a decrease in health care expenditures (Khan et al., 2020). The contemporary scientific literature is consistent in that sustainable and ecological lifestyles favor health care expenditure by minimizing these economic expenses through the promotion of healthy lifestyle habits (Lin et al., 2019; Yang et al., 2021). This evidence justifies the need to take into account environmental variables in the modeling of health care expenditures.

Increases in health care expenditures are of concern for the global economy and global health because they question and challenge the financial capacity of governments to provide sufficient, fair, and safe health care services for the general population (Meskarpour Amiri et al., 2021). Analyzing or replicating modifiable risk factors and environmental variables at a global and macro-political level is crucial for the development and application of health intervention and prevention models that improve health care expenditures while maintaining the quality of public medical services (Milani and Lavie, 2009). In addition, the incorporation of the analysis of environmental variables would also allow the identification of sustainable development goals (SDGs) that would be useful for the implementation of public health prevention policies (Sharma et al., 2021).

The present study provides a statistical analysis on global health with data from 154 countries. The objective of the research was to analyze the predictive functions relating to average alcohol consumption, economic expenditures on environmental damages, consumption and use of renewable energies, number of employees in sales positions (as an indicator of a country's economic productivity), and suicide rates with domestic general government health expenditure per capita (measured in US dollars). Considering the cited scientific literature, our main hypothesis is the following: environmental variables and alcohol consumption (as a modifiable risk factor) predict significant variations in health care expenditures, which also vary according to the political characteristics of each country. If this hypothesis is fulfilled, it will be possible to provide ratios and decision thresholds that can be used by governments and health authorities.

2. Methods

2.1. Ethics approval

The Committee of Ethical Guarantees of *Ramon Llull University* and *Blanquerna Foundation*, (Barcelona, Spain) reviewed, favorably evaluated, and approved this research. Likewise, the procedures of this study adhere to the Spanish Government Data Protection Organic Law 3/2018 and the Declaration of Helsinki of 1975, revised in 2013.

2.2. Sample of countries

The sample of this study consisted of 154 countries belonging to five geographical regions: 38 countries (25 %) are in Europe; 28 (18 %) in the Americas; 44 (28 %) in Africa; 35 (23 %) in Asia; and 9 (6 %) in Oceania. The sample sizes for each country can be found in Appendix A attached to this article as supplementary material. The other variables were measured from data provided by the public administrations of each country and were obtained through the two multinational companies that collaborated in this research. This information is explained in subsection 2.3.

2.3. Data access and measurement procedures

All the data for this research came from two international organizations in charge of digital data collection and management. Firstly, The World Bank (The World Bank. Products and Services. The World Bank;, 2022), collected indicators for each country (The World Bank. Products and Services. The World Bank;, 2022) related to 1) ERCDE, 2) annual alcohol consumption (measured in liters and average values), 3) renewable energy consumption rate, 4) domestic general government health expenditure per capita (measured in US dollars and average values), and 5) total suicide rate per 100,000 inhabitants.

The ERCDE variable requires clarification of a crucial detail: ERCDE was measured from the estimated millions of dollars attributable to damages caused by carbon dioxide emissions in each country. Therefore, these measurements do not represent the direct economic expenditures that governments spent to save the negative consequences of pollution. All these variables were quantitative-continuous.

Secondly, the multinational Graphext (Graphext. World Youth Map (private project). Graphext;, 2022) was commissioned, through a survey-based procedure, to collect measurements on the following variables (Graphext. World Youth Map (private project). Graphext;, 2022):

1) type of governance (0 authoritarianism, 1 weak democracy, and 2 democratic governance);
2) type of political ideology (1 right, 2 moderate-center, and 3 left);
3) sales employment ranking within the ten most predominant jobs in each country – Graphext was asked to record the 10 most prevalent types of jobs for each country. The variable "sales" was chosen as an economic indicator related to the productivity of each country. When the variable "sales" was ranked no. 1 in each country, 10 points were attributed to it. When the variable "sales" was ranked no. 10 (i.e. the last position), 0 points were attributed to it. Thus, using a metric scale from 0 to 10, this variable measured the degree to which the job "sales" was the most frequent in each country. If "sales" jobs were frequent it meant that the country generated import and export interaction flows and would therefore have a higher economic status;
4) the most searched Twitter topic categories over the last year. This would provide information on the impact of politics on the predominant digital culture in social networks. The classification categories were 1) Leisure activities (includes movies, TV Shows, sports, hobbies, etc.), 2) Education (for all educational levels and fields), 3) Aesthetic Topics (includes, clothing, jewelry, beauty, etc.), 4) Food (includes brands, restaurants, nutrition, diet, etc.), and 5) Electronics (includes videogames, mobiles, computers, etc.).

For the classifications of the type of governance and political ideology, the statistical indicators developed by the Economist Intelligence Unit (EIU) were used, among which we highlight The Democracy Index. The EIU indicators made it possible to objectify and operationalize these categories.

In order to facilitate the consultation and distribution of the variables, the raw data of this research is provided as an attachment in ".sav" file format. We remind you that the sample sizes associated with each country were specified in parentheses in the list of countries in the previous subsection.

All data collection was done online and from the mobile devices of each user. In the case of Twitter data, the accounts of each participant were analyzed using automatic programming procedures and computational methods. Volunteers from each of the countries that participated in this study signed an informed consent form that guaranteed completely anonymous data collection and processing.

In this research, no structured assessment tests were used to measure the variables. Therefore, we will not present a "materials or instruments" section in this report. The instruments were based on the cited multinational companies' own digital resources.

2.4. Statistical/data analysis

All the data were processed using various programs and programming languages: the SPSS statistical package was used to perform an initial debugging and preparation of the formal data matrix; the R programming language was also used (see (R Core Team, 2022) (R Core Team, 2022). The variables analyzed were those specified in the previous subsection. Multiple linear regression models were applied using the forward stepwise method as a decision criterion. This method allowed the development of a parsimonious and ecological prediction model to determine which variables modulated health care expenditures. Several analysis of variance models with fixed effects (ANOVAs) were also applied. The calculation of the explained variance of the ANOVA models was performed with the corrected partial eta squared coefficient. Nonlinear models based on logistic, cubic, and exponential functions were also fitted in order to refine the prediction and variations of the dependent variable healthcare expenditures. The mathematical expression that represented the logistic function was:

$$\widehat{y} = \frac{1}{1 + e^{\beta_0 + \beta_1 X}} \tag{1}$$

The equation for the cubic function was:

$$\widehat{y} = \beta_0 + \beta_1 X + \beta_2 X^2 + \beta_3 X^3 \tag{2}$$

Finally, the exponential function was mathematically notated as follows:

$$\widehat{y} = e^{\beta_0 + \beta_1 X} \tag{3}$$

The calculation of the explained variance of the regression models (linear and nonlinear) was performed with the corrected coefficient of determination (R^2). No outliers or anomalous values were identified in the prediction models and there were no missing values affecting the analyses. In these non-linear models and in the other statistical contrasts, a confidence level of 95 % (risk of error of 55) was used as a decision criterion.

2.5. Sample size previous estimation

The reference population for this study was the data associated with each of the countries. However, despite the large amount of data, there was a question as to how many minimum countries we should include in the study in order to be able to draw generalizations on a global scale. Since the total population of countries (population = 195) and the associated measurement error could be estimated concretely, the following equation was used as a criterion for estimating the minimum sample we needed to obtain:

$$n_{Countries} = \frac{\frac{z^2 \cdot p \cdot (1-p)}{e^2}}{1 + \left(\frac{z^2 \cdot p \cdot (1-p)}{e^2 \cdot N}\right)} \tag{4}$$

where

p is the confident level ($p = 0.95$);

z is the standardized value taking into account the confidence level (95 %, $z = 1.96$);

e is the estimated error in decimal metric ($e = 0.05$).

The result of the minimum sensitive sample to obtain a satisfactory contrast power was 53.3 total countries. Any n value above 53.3 would be adequate to ensure sample adequacy. We recall at this point that the number of countries registered in this study was 154.

3. Results

3.1. Political and governance effects

The first analysis tested whether the type of government (authoritarianism, democracy and flawed democracy) had an effect on health care expenditures. The analysis of variance showed significant results, $F_{Brown\text{-}Forsythe} = 36.918$, $p < 0.001$ (residual degrees of freedom = 83.568; explained variance = 23.1 %). Secondly, we tested whether the type of government affected the predictor variables: 1) alcohol consumption, 2) consumption rate of renewable energy, 3) suicide rate, 4) ERCDE and 5) sales ranking jobs. The results were as follows (in order of enumeration): 1) $F_{Brown\text{-}Forsythe} = 20.019$, $p < 0.001$ (residual degrees of freedom = 2040.066; variance explained = 20.5 %); 2) $F_{Brown\text{-}Forsythe} = 7.452$, $p < 0.001$ (residual degrees of freedom = 90.382; variance explained = 10.8 %); 3) $F_{Brown\text{-}Forsythe} = 4.335$, $p = 0.015 < 0.05$ (residual degrees of freedom = 130.646; variance explained = 5.1 %); 4) $F_{Brown\text{-}Forsythe} = 0.364$, $p = 0.695$ (residual degrees of freedom = 143.940; variance explained = 0.4 %); 5) $F_{Brown\text{-}Forsythe} = 6.503$, $p = 0.002 < 0.05$ (residual degrees of freedom = 124.305; variance explained = 8 %). The results were significant in all variables except for the suicide rate variable. Therefore, the hypothesis that the type of government affects the levels of the variables measured is maintained.

Finally, the degree of association between the most searched categories on Twitter (as an independent variable) and the six quantitative variables of 1) health care expenditure, 2) alcohol consumption, 3) renewable energy consumption, 4) suicide rates, 5) ERCDE, and 6) sales ranking jobs was also tested. The results were as follows (in order of enumeration): 1) $F_{Brown\text{-}Forsythe} = 2.024$, $p = 0.049 < 0.05$ (residual degrees of freedom = 52.343; variance explained = 0.7 %); 2) $F_{Brown\text{-}Forsythe} = 2.570$, $p = 0.031 < 0.05$ (residual degrees of freedom = 102.337; variance explained = 0.7 %); 3) $F_{Brown\text{-}Forsythe} = 1.835$, $p = 0.113 > 0.05$ (residual degrees of freedom = 94.652; variance explained = 0.5 %); 4) $F_{Brown\text{-}Forsythe} = 0.217$, $p = 0.955 > 0.05$ (residual degrees of freedom = 101.094; variance explained = 0.07 %); 5) $F_{Brown\text{-}Forsythe} = 0.330$, $p = 0.943 > 0.05$ (residual degrees of freedom = 77.591; variance explained = 0.08 %); and 6) $F_{Brown\text{-}Forsythe} = 0.845$, $p = 0.520 > 0.05$ (residual degrees of freedom = 115.134; explained variance = 2.7 %). It is concluded that only marginally significant results were obtained for the variables health care expenditure and alcohol consumption. The alternative hypothesis that Twitter trends are associated with these two variables is maintained. Table 1 shows the descriptive statistics of the variables and the post-hoc paired comparison tests using the Bonferroni correction in all cases.

Fig. 2 illustrates which countries invested more money in the public health system in recent years.

3.2. Modeling health care expenditures: linear and nonlinear regressions

The first step to know the best mathematical representation of the relationship between the variables is to calculate Pearson's linear correlation coefficients. This information is presented in Table 2.

The highest correlations were considered to fit initial linear regression models. The aim of these models was to predict health care expenditures. According to Table 2, the predictor variables chosen were alcohol consumption, ERCDE and sales ranking jobs. Table 3 shows the multiple regression models using the forward stepwise method. In this Table, the estimation of the parameters, the explained variance, and the analysis of the changes in the explained variance are given.

The linear model that best predicts healthcare expenditures is number 3, which includes the three predictor variables chosen from the linear correlations. In total, the model is able to predict 33.1 % of the increases in healthcare expenditures. However, considering models 1 and 2 in Table 3, it is important to note that the alcohol consumption variable was the most effective predictor variable or the one that contributed the greatest amount of variance explained. In contrast, the ERCDE variable has an excessively low regression coefficient associated with it. This means that regression models 2 and 3 can be useful models for estimating changes in health care expenditures, given that the contribution of ERCDE was minimal (although significant).

Although the percentage 28.3 % and 33.1 % were not excessively

Table 1
Descriptive statistics and post-hoc tests of pairwise comparisons.

Independent variable: type of government				
Dependent variables	Groups (number of countries)	Means	Standard deviations	Significant comparisons
Health care expenditures	A - Authoritarianism (n = 40)	202.61	366.409	A vs B, t = -5.416, p < 0.001
	B - Democracy (n = 71)	1.437.11	1.659.537	B vs C, t = 5.707, p < 0.001
	C - Flawed democracy (n = 43)	165.78	252.350	
Alcohol consumption	A - Authoritarianism (n = 40)	4.23	3.483	A vs B, t = -5.413, p < 0.001
	B - Democracy (n = 71)	8.16	3.795	B vs C, t = 4.893, p < 0.001
	C - Flawed democracy (n = 43)	4.68	3.647	
Renewable energy consumption	A - Authoritarianism (n = 40)	39.11	34.675	A vs B, t = 3.157, p = 0.006 < 0.05
	B - Democracy (n = 71)	23.23	16.437	B vs C, t = -3.837, p < 0.001
	C - Flawed democracy (n = 43)	42.10	27.621	
Suicide rates	A - Authoritarianism (n = 40)	8.20	6.278	B vs C, t = -1.969, p = 0.027 < 0.05
	B - Democracy (n = 71)	10.53	6.542	
	C - Flawed democracy (n = 43)	7.46	4.648	
ERCDE	A - Authoritarianism (n = 40)	4.002E + 9	1.147E + 10	There no were significant comparisons.
	B - Democracy (n = 71)	6.808E + 9	2.401E + 10	
	C - Flawed democracy (n = 43)	5.040E + 9	1.641E + 10	
Sales ranking jobs	A - Authoritarianism (n = 40)	4.800	3.098	A vs B, t = -3.6122, p < 0.001
	B - Democracy (n = 71)	6.817	2.820	
	C - Flawed democracy (n = 43)	5.953	2.554	
Independent variable: most searched Twitter categories[a]				
Dependent variables	Groups (number of countries)	Means	Standard deviations	Significant comparisons
Health care expenditures	A - Aesthetic topics (n = 21)	994.249	1.532.508	F vs C, t = 3.076, p = 0.038 < 0.05
	B - Education (n = 24)	950.727	1.554.748	
	C - Electronics (n = 18)	124.812	247.331	
	D - Food (n = 23)	557.512	776.605	
	E - Leisure activities (n = 56)	703.719	1.218.621	
	F - Others (n = 12)	1.591.089	1.991.042	
Alcohol consumption	A - Aesthetic topics (n = 21)	7.457	3.125	A vs C, t = 3.191, p = 0.026 < 0.05
	B - Education (n = 24)	6.160	3.866	
	C - Electronics (n = 18)	3.345	2.630	
	D - Food (n = 23)	6.580	4.316	
	E - Leisure activities (n = 56)	6.349	4.518	
	F - Others (n = 12)	6.501	4.185	
Renewable energy consumption	A - Aesthetic topics (n = 21)	26.255	19.089	There no were significant comparisons.
	B - Education (n = 24)	32.353	23.206	
	C - Electronics (n = 18)	48.909	34.612	
	D - Food (n = 23)	30.792	25.693	
	E - Leisure activities (n = 56)	31.990	27.974	
	F - Others (n = 12)	26.343	23.079	
Suicide rates	A - Aesthetic topics (n = 21)	8.205	6.299	There no were significant comparisons.
	B - Education (n = 24)	9.775	5.161	
	C - Electronics (n = 18)	9.183	5.085	
	D - Food (n = 23)	9.661	8.251	
	E - Leisure activities (n = 56)	8.766	5.986	
	F - Others (n = 12)	9.275	5.865	
ERCDE	A - Aesthetic topics (n = 21)	3.478E + 9	7.259E + 9	There no were significant comparisons.
	B - Education (n = 24)	2.836E + 9	5.006E + 9	
	C - Electronics (n = 18)	8.479E + 9	2.490E + 10	
	D - Food (n = 23)	6.440E + 9	1.466E + 10	
	E - Leisure activities (n = 56)	6.171E + 9	2.613E + 10	
	F - Others (n = 12)	6.064E + 9	1.382E + 10	
Sales ranking jobs	A - Aesthetic topics (n = 21)	6.619	2.991	There no were significant comparisons.
	B - Education (n = 24)	5.417	3.243	
	C - Electronics (n = 18)	5.222	2.881	
	D - Food (n = 23)	6.348	2.917	
	E - Leisure activities (n = 56)	6.125	2.880	
	F - Others (n = 12)	6.667	2.498	

Notes: ERCDE = Economic reversal of the environmental damage caused by carbon dioxide emissions.
a. Complementary statistical analysis.
Warning: Some numerical values are too large to express completely in this table. In these cases the following expression was used: $E \pm n = 10^{(n)}$. Example: 4.002E + 9 = 4.002×10^9 = 4002,000,000.

small, we consider that they could be statistically improved if we fit curvilinear or nonlinear regression models. In addition, there are still 2 predictor variables – renewable energy consumption and suicide rates – to include in the prediction model. So, the next step was to calculate the R^2 fit index associated with the cubic, exponential and logistic functions of the 5 original predictor variables. It was decided to graphically represent those functions that provided the greatest variance explained in the prediction of health care expenditures. This information can be found in Table 4.

The results in Table 4 indicate that the function that best predicted health care expenditures was the cubic function, with the exception of the predictor variable renewable energy consumption, for which the best models were those presenting the logistic and exponential functions. Considering the smaller standard errors associated with the parameters, the exponential function was chosen for this variable (instead of the logistic function) as the one that represented the prediction of health care expenditures with smaller errors. The percentages of variance explained fluctuate between 16.5 % and 35.22 %. Fig. 3 shows graphically the nonlinear functions of the variables in Table 4.

The estimated parameters of the predictor variable renewable energy

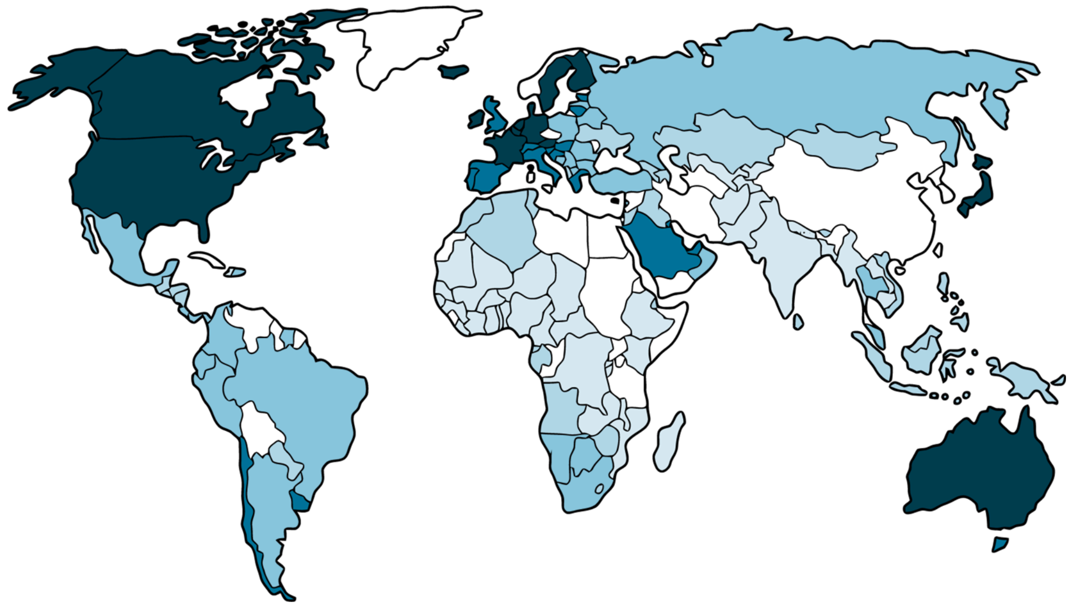

Fig. 2. World map of countries applying the highest and lowest health care expenditures per person per year (2018–2021). The ranking of the colors is as follows: darkest blue (3501–5414 US dollars); dark blue (733–3500 US dollars); moderate blue (191–732 US dollars); light blue (33–190 US dollars); and lightest blue (0–32 US dollars). The world map was elaborated, manually drawn, and created from the global data by Prof. Álex Escolà-Gascón. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Linear correlations.

	1	2	3	4	5	6
1. Renewable energy consumption	—					
2. ERCDE	−0.181	—				
3. Suicide rates	−0.017	0.186	—			
4. Alcohol Consumption	−0.146	0.115	0.391*	—		
5. Sales ranking jobs	−0.205	0.123	0.175	**0.346***	—	
6. Health care Expenditures	−0.218	**0.302***	0.263	**0.474***	**0.408***	—

Notes: ERCDE = Economic reversal of the environmental damage caused by carbon dioxide emissions. *p < 0.01.

Table 4
Explained variance (adjustment) of the nonlinear models. Health care expenditures are predicted.

	Linear R^2	Cubic R^2	Exponential R^2	Logistic R^2
1. Renewable energy consumption	4.7 %	6.4 %	35.2 %	35.2 %
2. ERCDE	9.1 %	16.5 %	3.6 %	3.6 %
3. Suicide rates	6.9 %	19 %	9 %	9 %
4. Alcohol Consumption	22.4 %	29.9 %	29.1 %	29.1 %
5. Sales ranking jobs	16.6 %	27.9 %	23.5 %	23.5 %

Notes: ERCDE = Economic reversal of the environmental damage caused by carbon dioxide emissions. *p < 0.01.

Table 3
Linear regression model using forward step-wise method in order to predict health care expenditures.

M	Predictors	B_0	$\beta_{Unstandardized}$ (errors)	$\beta_{Standardized}$	R^2 (changes in R^2)	F Change (critical level)	Errors of the estimation models
1	Alcohol Consumption	−169.768	151.030 (22.769)	0.474 (p < 0.001)	21.9 % (-)	43.998 (p < 0.001)	1153.654
2	Alcohol Consumption	−729.882	120.496 (23.260)	0.378 (p < 0.001)	28.3 % (Δ6.8 %)	14.418 (p < 0.001)	1105.875
	Sales ranking jobs		123.660 (32.567)	0.277 (p < 0.001)			
3	Alcohol Consumption	−720.987	114.483 (22.539)	0.359 (p < 0.001)	33.1 % (Δ5.2 %)	11.791 (p = 0.001)	1068.359
	Sales ranking jobs		113.983 (31.588)	0.255 (p < 0.001)			
	ERCDE		1.553E-8 (≈0)	0.231 (p = 0.001)			

Notes: M = predictive models; ERCDE = Economic reversal of the environmental damage caused by carbon dioxide emissions. *p < 0.01.
Warning: Some numerical values are too large to express completely in this table. In these cases the following expression was used: E ± $n = 10^{(n)}$. Example: 1.553E - 8 = $1.553x10^{(-8)}$ = 0.00000001553.

consumption were β_0 = 697.521, β_1 = -0.044 (error = 0.005), $\beta_{1\text{-Standarized}}$ = -0.593, estimation error = 1.619. The estimated parameters of the predictor variable ERCDE were β_0 = 500.933, β_1 = 9.523E-8[2] (error = ≈0), β_2 = -1.663E-18 (error = ≈0), β_3 = 6.674E-30 (error = ≈0), $\beta_{1\text{-Standarized}}$ = 1.408, $\beta_{2\text{-Standarized}}$ = -4.095; $\beta_{3\text{-Standarized}}$ = 3.099, estimation error = 1204.713. The parameters of the suicide rate variable were β_0 = -6.486, β_1 = 13.393 (error = 127.387), β_2 = 15.082 (error = 10.996), β_3 = -0.571 (error = 0.265), $\beta_{1\text{-Standarized}}$ = 0.063, $\beta_{2\text{-Standarized}}$ = 1.874;, $\beta_{3\text{-Standarized}}$ = -1.848, estimation error = 1187.176. The parameters of the alcohol consumption variable were β_0 = 499.213, β_1 = -354.337 (error = 135.833), β_2 = 71.918 (error = 18.142), β_3 = -2.639 (error = 0.669), $\beta_{1\text{-Standarized}}$ = -1.112, $\beta_{2\text{-Standarized}}$ = 3.243, $\beta_{3\text{-Standarized}}$

[2] Some numerical values are too large to express completely in the text. In these cases the following expression was used: E ± n = $10^{(n)}$. Example: 9.523E − 8 = $9.523x10^{(-8)}$ = 0.00000009523.

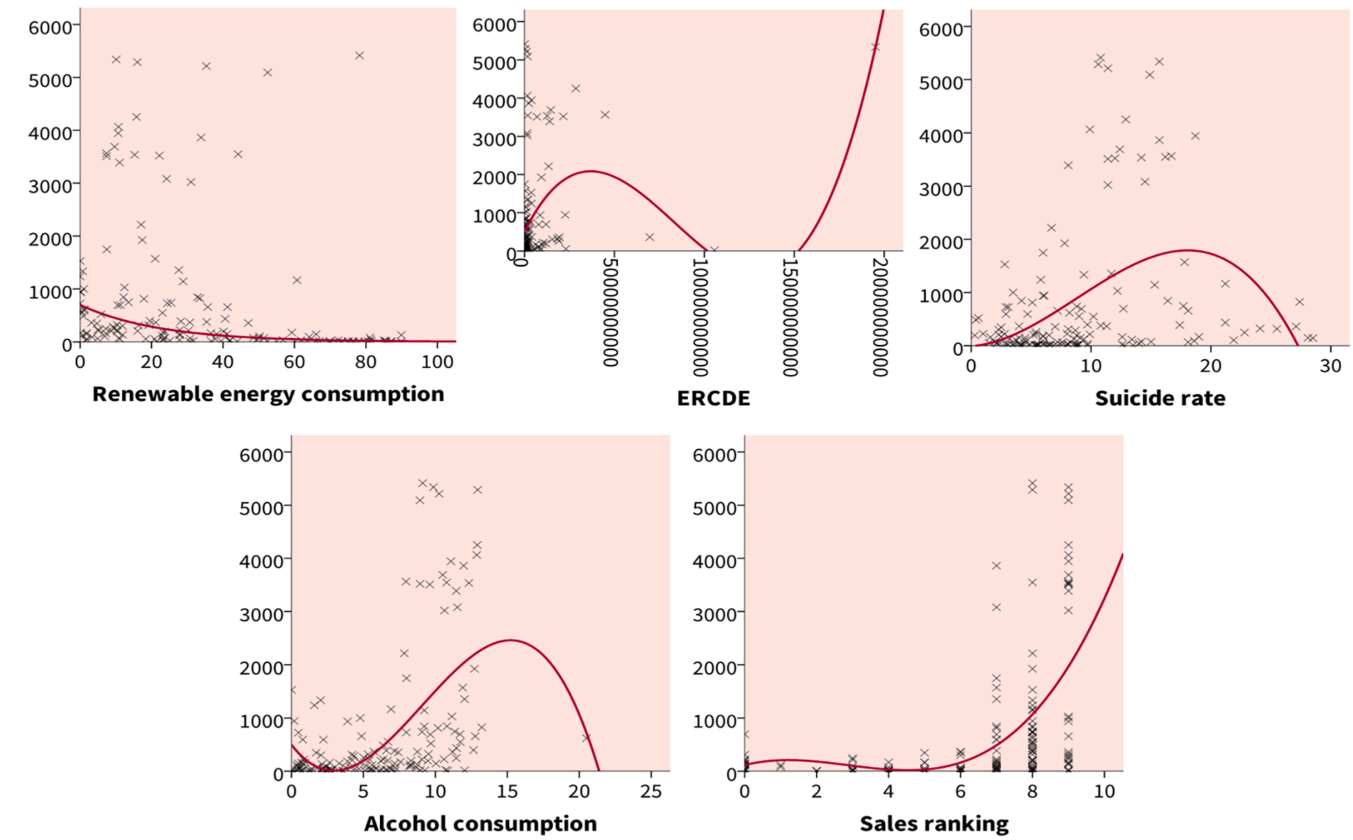

Fig. 3. A set of nonlinear functions that allow predicting health care expenditures between 16.5% and 35.22%. The functions shown are cubic, except for the function applied to the renewable energy consumption variable, which was exponential.

= -1.824, estimation error = 1104.263. Finally, the parameters of the variable sales ranking were β_0 = 115.259, β_1 = 170.352 (error = 287.542), β_2 = -89.099 (error = 76.626), β_3 = 10.339 (error = 5.412), $\beta_{1\text{-Standarized}}$ = 0.382, $\beta_{2\text{-Standarized}}$ = -1.910, $\beta_{3\text{-Standarized}}$ = 2.041, estimation error = 1120.123.

With these results, and considering the weights in Table 4, the predictor variable that best allows us to model health care expenditures is renewable energy consumption, which shows an exponentially decreasing trend. This means that, as renewable energy consumption increases, health care expenditures tend to decrease exponentially by 35.22 %. The variables alcohol consumption and sales ranking also showed explained variances>20 %, which is a weight that also allows us to consider them as useful variables for modelling health care expenditures. These two factors have increasing and decreasing trends in the curves due to the cubic property of both functions. The discussion section will interpret these trends in more detail.

Therefore, with the results presented, sufficient evidence was found to support the maintenance of the research hypothesis of this study. In addition, the relationship between environmental variables and modifiable risk factors with health care expenditure has increasing and decreasing trends that allow us to specify certain inflection points in the curves. These inflection points could be used as guidelines for decision making at the global level.

4. Discussion

The evidence found in this study is in line with other research that studied the relationship between risk factors, environmental variables, and health expenditures (Bouchery et al., 2011; Apergis et al., 2018; Liu and Ao, 2021; Sahoo and Sethi, 2021). According to the predictor variables, health care expenditures have linear and nonlinear interpretations. Below we present some ratios and cut-off points that can be useful in reducing the health care expenditures of each country.

4.1. Ratios and linear inferences

The linear inferences are the most stable, but they also provide the smallest explained variances: Δ21.9 % for alcohol, Δ6.8 % for sales ranking Jobs and Δ5.2 % for ERCDE). In total, the above three variables predict 33.1 % increases in healthcare expenditures (see model 3, Table 3). Considering multiple regression model number 3, we find that average healthcare expenditures per person will systematically increase $114.483 for each liter of pure alcohol consumed per individual. This increase will occur when 1) sales jobs occupy the 4th position among the 10 most frequent types of jobs in the country, and 2) economic expenditures attributed to material damages from carbon dioxide emissions (ERCDE) are close to 5,585,867,726 million US dollars. Similarly, health expenditures will increase by $113.983 for each position (within a ranking of 10) that sales jobs in a country increases. This linear trend will occur when the number of liters of alcohol per person for 1 year is close to 6 and when the annual expenditures associated with ERCDE are similar to $5,585,867,726 for each country.

Finally, by keeping alcohol consumption levels in check at around 6 L and sales jobs in the fourth position in the top 10 most common jobs in each country, health economic spending per person will only increase by $0.00000001553 for every $1.00 attributable to property damage caused by carbon dioxide emissions. It should be noted that this ratio will annually increase health care spending per person by $1.553 for every $100,000,000 (one hundred million) attributable to ERCDE. These health economic expenditures per person should be multiplied by the amount of a country's total population. The result will be the total amount of dollars that a country should increase in 1 year in its health budget. As a conclusion of the multiple linear regression, it should be noted that by reducing alcohol consumption by 1 unit (i.e. by reducing 1

L per person per year), by diversifying employability (i.e. by reducing the sales job by 1 position in the ranking) and by reducing the material damage attributable to CO_2 emissions (i.e. for each US dollar we reduce in material damage), health care expenditures would be reduced by an average of $228.466 per person and per year.

4.2. Suggested cut-off points from nonlinear models

The interpretation of nonlinear analyses should focus on those predictor variables that contributed an explained variance of health care expenditures>20 % of the variance. Variables with lower explained variance rates may not have practical implications for policy decisions, but that does not mean that they are not relevant. Due to editorial limitations related to the length of the reports, it was decided to interpret and provide cut-off points for the three predictor variables that explained>20 % of the variance.

First, the rate of renewable energy consumption was the variable that predicted the greatest variance of health care expenditures (35.2 %). The trend of this relationship is decreasing until the rate of renewable energy consumption reaches values close to 60 %. This is an inflection point from which the trend of the function curve tends to uniformity. Beyond this threshold, healthcare costs do not decrease significantly.

Identifying and understanding these trends on a global scale is crucial because it reinforces the evidence provided by those studies that advocated greening as a beneficial indicator for population health (Khan et al., 2020) and is associated with reductions in health care expenditure (Yang et al., 2021). If CO_2 emissions are related to consumerist lifestyles (Zhang et al., 2020) and to increases in health care expenditures (Gündüz, 2020; Lenzen et al., 2020), the consumption of renewable energies could be associated with other population lifestyles that favor well-being and the reduction of health care expenditure. In fact, the consumption of renewable energies can be understood as a global indicator of the ecological levels of each country (Iddrisu and Bhattacharyya, 2015). The more renewable energies a country uses, the more and better it will be contributing to the environment, and at the same time promoting ecological lifestyles and alternatives to classic consumption policies. With the results obtained, we can scientifically establish a non-linear relationship between the use of renewable energies and the health budgets of each of the 154 countries included in this study. However, knowing that reductions in healthcare costs are no longer significant after 60 %, one might ask, what are the implications for health at this cut-off point?

Secondly, alcohol consumption has an initial decreasing relationship with health care expenditures. From the consumption of 4–5 L of alcohol per person during the period of 1 year, the trend of health care expenditures begins to increase. This growth does not vary until 14–15 L of alcohol are reached, at which point the trend of the curve changes and health care expenditures decrease. This last decreasing trend should be interpreted with caution since few countries showed alcohol consumption levels above 13–14. This could imply that the estimates of the forecasts in this last trend were unstable (Escolà-Gascón, 2022).

These increasing and decreasing trends predict changes in the levels of health care expenditures by 29.9 %. According to these inflection points, it appears that alcohol consumption below 4–5 L per person over 1 year does not have negative consequences for health care expenditure (which does not mean that it does not have negative consequences for health (Burton and Sheron, 2018). It is at these thresholds that an increasing relationship would begin (as we have already discussed in the previous linear analysis) and health care expenditure would increase.

Third, the trend of the curve in the sales ranking variable initially increases, followed by a decreasing slope from score 2 onwards. The most significant change in the trend of the curve occurs at levels 5–6 of this variable. It is at these thresholds that health care expenditures suddenly increase. These increasing and decreasing fluctuations allow us to estimate the changes in health care expenditures at 27.9 %. We can determine that the countries that have sales jobs within the ranking of the 4 most frequent jobs will be those with the highest health care expenditures. Consequently, this suggests the need to diversify employment typologies and not limit them to the field of production and commerce – this suggestion is also in line with the *sustainable development goals* (SDGs) (Sharma et al., 2021). In general, it is concluded that these three variables individually and by means of cubic relationship models (and exponential for the renewable energy consumption variable), predict health care expenditures with greater and better efficiency.

4.3. Political and social implications

The analyses and results in Table 1 report the effects of government type on health care expenditures and the other predictors. Democratic countries are those with the highest health care expenditures (compared to countries governed by authoritarian systems and weak democracies). The fact that a country has a democratic government explains 23.1 % of the increases in health care expenditures. This result could be explained by the fact that non-democratic governments are those that invest the least in people's health and, therefore, also represent the countries with the highest mortality rates (Al-Azri et al., 2020). However, the challenge that arises when examining the possibility of reducing health care expenditures is not based on challenging public health services to the citizenry. Rather, the challenge is how to reduce these expenditures without the need to detract from the quality of the health services offered. Thus, it should be noted that the problem is not in democratic governance, but in the consequences of policies based on consumerism (which affects lifestyles (Zhang et al., 2020) and massive industrialization (which promotes increases in CO_2 emissions and health care expenditures (Leigh et al., 2005).

Paradoxically, democratic governments have the highest suicide rates (10.53 %, compared to 7.46 % for governments with weak democracies) and the lowest renewable energy consumption rates (23.23 % of total energy consumption, compared to 42.10 % for countries with weak democracies). In addition, the implementation of democratic governments explains by 8 % that sale jobs are the predominant employment type (the variable that allows predicting health care expenditures). Finally, democratic states are those that consume the most alcohol (8.16 L of alcohol per person per year, compared to 4.23 L consumed by authoritarian states). This figure, in addition to the harmful consequences for health, exceeds the inflection point derived from the cubic function based on alcohol consumption (4–5 points), which encourages health care expenditures to continue to rise. In addition, since 2018 the populations of the countries that consumed the most alcohol "tweeted" on social media platform Twitter topics relating to aesthetics (car brands, clothing brands and jewelry) which occupied the #1 position in the ranking of the most searched topics on Twitter. This trend provides a global understanding of what content alcohol consumption is related to. The other Twitter search trends had no significant effect on the variables analyzed in this study.

4.4. Final conclusions

Unlike other research that analyzed the same or similar variables, in this study the data, analysis, and results have a global impact and interpretation. Our research informs on the current state of health care expenditures around the globe and have a mainly organizational and structural application. Thus, the conclusions we provide below are addressed to healthcare organizations and political decision makers.

Firstly, we highlight the linear relationship between alcohol consumption, ERCDE and the predominance of sales jobs as variables that predict systematic increases in health care expenditures with a weight of 33.1 % in most of the 154 countries included in this study. If policymakers were to promote reductions in alcohol consumption, ERCDE, and sales jobs they would reduce health care expenditures by $228.466 per person and year. This reduction would not harm the quality of current health care services. Therefore, public policies that include the management of these variables as priority sustainable development goals (SDGs) in government decisions are required.

Secondly, we found that the consumption of renewable energies has an exponentially negative relationship with health care expenditures. The use of renewable energies would reduce the ecological footprint, promoting the prevention of people's health and the decrease of health care expenditures with a weight of 35.2 %. In this conclusion, it should be noted that the decreasing trend in health care expenditures from renewable energies becomes uniform when consumption rates reach values close to 60 %.

Lastly, we revealed that the relationships of the variables in this study with health care expenditures are not limited to linear or exponential trends. Cubic mathematical models showed that the predominance of sales jobs explains health care expenditures by 27.9 %, alcohol consumption increases its predictive capacity to 29.9 %, and suicide rates explain 19 %. Therefore, we propose that future research should analyze the political and health applicability of the inflection points observed in the increasing and decreasing trends of the functions in Fig. 2. It is important to provide evidence-based decision coordinates for health professionals and government authorities to favor a real sociopolitical change towards a green and environmentally sustainable system.

In general, these results reveal that democracies represent the type of government with the most imbalances in the interactive flows between economic, health and environmental systems. According to our evidence, it is necessary that power summits and political alliances between countries take into account the regularization of alcohol consumption, the priority use of renewable energies, and the diversification of employment (avoiding focusing on sales, and trade or production jobs, or both) in order to reduce health care expenditures while maintaining (or improving) the level of quality of current health services in each country.

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6. Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

CRediT authorship contribution statement

Álex Escolà-Gascón: Conceptualization, Data curation, Writing – original draft, Methodology, Writing – review & editing, Software. **Josep Lluís Micó-Sanz:** Conceptualization, Data curation, Visualization, Investigation. **Andreu Casero-Ripollés:** Supervision, Resources, Validation, Visualization.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pmedr.2022.102036.

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