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Architecture of the health system as an enabler of better wellbeing

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Abstract
Introduction. Health systems worldwide have heterogenous capacities and financing characteristics. No clear empirical evidence is available on the possible outcomes of these characteristics for population wellbeing.
Aim. The study aims to provide empirical insight into health policy alternatives to support the development of health system architecture to improve population wellbeing.
Method and results. We developed an unsupervised neural network model to cluster countries and used the Human Development Index to derive a wellbeing model. The results show that no single health system architecture is associated with a higher level of population wellbeing. Strikingly, high levels of health expenditure and physical health capacity do not guarantee a high level of population wellbeing and different health systems correspond to a certain wellbeing level.
Conclusions. Our analysis shows that alternative options exist for some health system characteristics. These can be considered by governments developing health policy priorities.

Key words
- population wellbeing
- health system capacity
- public health system
- health policy
- neural networks

INTRODUCTION

Health systems have an increasingly important role in national economies. Developed countries with higher income levels are willing to spend more on health systems and, because the average age of populations is getting higher, have a greater need for health care for elderly people. Growing populations in developing countries is another significant driver of demand for health care. In response to the increasing role of the healthcare services in national economies, governments have developed a range of different health systems [1, 2].

The current literature highlights the complexity of measuring the quality of health care services and the effectiveness of strategies to improve healthcare practices in developed countries [3, 4], particularly low-income and middle-income countries [5]. The World Health Organization (WHO) has reported heterogeneity in healthcare characteristics and in the effectiveness and implementation of healthcare quality strategies across Europe [6]. In addition, the leadership and governance of population health management and health payment systems varies across countries [7, 8]. For various reasons, including low satisfaction of healthcare service users [9], there is a clear demand to transform healthcare services towards more sustainable health and population wellbeing systems [10]. Furthermore, the COVID-19 pandemic has increased the focus on health system sustainability [11, 12].

Economic wellbeing is often measured by gross domestic product (GDP) per capita, which approximates the level of economic development. However, GDP per capita as a measure of economic development is only one driver of population wellbeing. To overcome this limitation, another measure of population wellbeing could be considered, such as the Human Development Index (HDI). The HDI takes into account that the criteria for assessing a country's development should encompass people and their capabilities and not only economic growth [13]. Wellbeing is a multidimensional condition that encompasses social, material, spatial and other conditions. It can be assesses using asset-based and health capability approaches [14]. Maintaining and contributing to wellbeing requires multidimensional actions with environmental, physical and/or psychological components, for example the use of urban public spaces for relaxation, education or recreation [15]. Overall wellbeing comprises three layers: personal, community and societal wellbeing. These layers are interconnected, but may compete for scarce

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resources [16]. Health and wellbeing are interlinked in quality of life measures that form the basis of public interventions (including for health, public health and social care), and are used as a combined dimension to evaluate health policy interventions [17, 18]. Wellbeing has already been adopted as a development goal to "deliver human and ecological wellbeing" within national development and wellbeing frameworks, including in Finland, Iceland, New Zealand, Scotland and Wales, within the Wellbeing Economy Governments initiative [16].

A wider framework has been introduced to assist in planning and evaluating development policies towards the 2030 Agenda for Sustainable Development [19]. Some studies have investigated different aspects of improvements in health systems and population wellbeing in different countries [20-22] by analysing factors such as the financial characteristics of health systems, as related to the prices of and expenditure on different health inputs such as medical equipment, medicines and health services. Other studies have investigated physical health capacities, efficiencies, and impacts on economic efficiency or reasons for inefficiency. Digitalization of health systems (e.g., electronic health records) can positively impact on healthcare quality [23]. Although both aspects of health systems are subject to health policy, so far there is little or no evidence or analysis linking them to population wellbeing.

This study analysed the architecture of national health systems using aggregated country data to investigate whether health system characteristics are linked to population wellbeing and, if so, in which combination. Health policy-makers are encouraged to promote specific health practices, such as increasing health system capacity and health financing, with the aim of increasing population wellbeing. However, the question remains of whether health systems with similar architecture can achieve similar levels of population wellbeing, and whether there might be a non-linear prerequisite for improving health system architecture. We focused on two specific research questions (RQs):

- RQ1: do specific characteristics of national health systems influence population wellbeing?
- RQ2: can similar levels of population wellbeing be achieved through different health system architectures?

This study addresses trade-offs between health system indicators in policies to enhance population wellbeing. Firstly, existing secondary data on financial characteristics and capacity characteristics of health sectors were analysed over time for a global sample of countries to provide robust results. Secondly, a methodological approach based on neural networks enabled us to determine the impact of input variables on the results. Finally, the study provides empirical evidence to help policy-makers to make decisions on designing health system architecture. The initial development of health systems and targets for population wellbeing can be important for the further evolution of health systems. However, the results show that different policy approaches can achieve similar levels of population wellbeing.

MATERIALS AND METHODS

Data variables

Variables were selected based on theoretical reasoning. Therefore, unlike in a classical econometric approach, a priori elimination of variables resulting from possible multicollinearity or outliers was not needed. Variables were selected to reflect characteristics of health system financing and national healthcare capacities. The final selection of variables was based on the availability of national data.

Available data for years between 1990 and 2019 on the two groups of variables were collected for a global sample of 45 countries *(Table 1)*. The number of years of available data varied from 8 years for Belgium and Canada to 3 years for Mexico and 2 years for Burkina Faso. However, data for 6 or 7 years were available for most countries. *Table 1* lists the annual data included in the analysis by country. A total of 283 observations was included in the final database.

Next, the data were sorted into two groups: those describing population wellbeing and those describing health system architecture. To assess population wellbeing, we considered multiple global measures and indexes to determine the general level of population wellbeing for each country and year. Based on the composition, availability, reliability and consistency of the data, we decided to use the United Nations Development Programme's HDI [13]. The HDI has three dimensions: (1) long and healthy life, (2) knowledge and (3) a decent standard of living. Each dimension has one or more indicators: life expectancy at birth (in years) for the first dimension, expected years of schooling (in years) and mean years of schooling (in years) for the second dimension, and gross national income per capita in 2017 purchasing power parity in US dollars for the third dimension (using the natural logarithm to reflect the diminishing importance of income). For each dimension, an individual dimension index was calculated and the HDI was given as the geometric mean of the indices for all three dimensions [13, 24]. We obtained HDI values from the Data Center of the United Nations Development Programme [25].

In the second group (health system architecture), we used selected variables to describe the financing characteristics and capacity of each country's health system. Health outcome indicators were deliberately omitted because this study assessed health system architecture as related to healthcare policy. To ensure that data were reliable and comparable across countries, all variables were obtained from a single source, the WHO [26]. Within these parameters, data were obtained for 11 variables *(Table 2)*. The possibility of double counting particular characteristics of health sector architecture and population wellbeing or any of its dimensions was minimised by ensuring that the HDI dimensions did not include any of the 11 selected variables of health system architecture. The 12 selected variables describe health system financing (such as different categories of health expenditure) and health sector capacities (such as numbers of different types of medical experts and number of hospital beds).

Table 1
Included countries, showing the years of available data

Country	Code	Year								Number of observations
		1990	2000	2010	2014	2015	2017	2018	2019	
United Arab Emirates	ARE	X	X	X	X	X	X			6
Australia	AUS	X	X	X	X	X				5
Austria	AUT	X	X	X	X	X	X	X		7
Belgium	BEL	X	X	X	X	X	X	X	X	8
Burkina Faso	BFA		X	X						2
Bangladesh	BGD	X	X	X	X	X				5
Canada	CAN	X	X	X	X	X	X	X	X	8
Switzerland	CHE	X	X	X	X	X	X	X		7
Chile	CHL	X	X	X	X	X	X	X		7
Colombia	COL	X	X	X	X	X	X	X		7
Czechia	CZE	X	X	X	X	X	X	X		7
Germany	DEU	X	X	X	X	X	X			6
Dominican Republic	DOM	X	X	X	X	X	X			6
Spain	ESP	X	X	X	X	X	X	X		7
Estonia	EST	X	X	X	X	X	X	X		7
France	FRA	X	X	X	X	X	X	X		7
United Kingdom	GBR	X	X	X	X	X	X	X	X	8
Georgia	GEO		X	X	X					3
Greece	GRC	X	X	X	X	X	X	X		7
Hungary	HUN	X	X	X	X	X	X	X		7
Indonesia	IDN	X	X	X	X	X	X			6
Ireland	IRL	X	X	X	X	X	X	X		7
Iceland	ISL	X	X	X	X	X	X	X	X	8
Israel	ISR	X	X	X	X	X	X	X		7
Italy	ITA	X	X	X	X	X	X	X		7
Jordan	JOR	X	X	X	X	X	X			6
Republic of Korea	KOR	X	X	X	X	X	X	X		7
Sri Lanka	LKA	X	X	X	X	X	X			6
Lithuania	LTU	X	X	X	X	X	X	X		7
Latvia	LVA	X	X	X	X	X	X	X		7
Republic of Moldova	MDA	X	X	X	X					4
Mexico	MEX	X	X	X						3
Myanmar	MMR	X	X	X	X	X	X			6
Montenegro	MNE			X	X	X	X			4
Netherlands	NLD	X	X	X	X	X	X	X		7
Norway	NOR	X	X	X	X	X	X	X		7
New Zealand	NZL	X	X	X	X	X	X	X	X	8
Oman	OMN		X	X	X	X	X			5
Pakistan	PAK	X	X	X	X	X	X			6
Panama	PAN	X	X	X	X	X				5
Saudi Arabia	SAU	X	X	X	X	X	X			6
Slovakia	SVK	X	X	X	X	X	X	X		7
Slovenia	SVN	X	X	X	X	X	X	X		7
Trinidad and Tobago	TTO	X	X	X	X	X	X			6
Türkiye	TUR	X	X	X	X	X	X	X		7
Total number of observations										283

Table 2
Two groups of used variables

	Wellbeing
1	HDI – Human Development Index
	Health system's architecture
1	UHC Service Coverage Index (SDG 3.8.1)
2	Hospital beds (per 10,000 of population)
3	External health expenditure (EXT) as a percentage of current health expenditure (CHE), in %
4	Out-of-pocket expenditure as a percentage of current health expenditure (CHE), in %
5	Current health expenditure (CHE) as a percentage of gross domestic product (GDP), in %
6	Domestic general government health expenditure (GGHE-D) as a percentage of gross domestic product (GDP), in %
7	Domestic general government health expenditure (GGHE-D) as a percentage of general government expenditure (GGE), in %
8	Pharmacists (per 10,000 of population)
9	Dentists (per 10,000 of population)
10	Medical doctors (per 10,000 of population)
11	Nursing and midwifery personnel (per 10,000 of population)

Source: data on HDI were obtained from the United Nations Development Programme (https://hdr.undp.org/data-center/documentation-and-downloads); data on health system architecture were obtained from the World Health Organization (https://www.who.int/data/gho/data/indicators).

Self-organizing map clustering model

For our analysis, we designed a modelling procedure. We first develop a clustering model based on Kohonen's self-organizing map (SOM) method [27], which has been widely used to cluster scientific data in its original or modified form or combined with other methods (for example, see references [28-32]). Kohonen's SOM creates an artificial neural network based on an unsupervised learning algorithm in which the neurons compete with one another to correspond to the data. Data with similar characteristics are ordered to the same or a neighbouring node of the map. The SOM can form a one-, two-, or three-dimensional network of nodes; higher dimensions are also possible but not reasonable. For a further details of three-dimensional models and network topologies, see Jagric and Zunko [33]. The network learns via an iterative procedure in which learning data are presented to the network in a random order in each iteration. Thus, multidimensional input data are transformed into a lower-dimension output map or pattern array, usually (as in our case) a two-dimensional network [27, 29, 30].

In this study we designed a SOM of 20×20 neurons in size. The neurons were positioned on the two-dimensional network via hexagonal ordering, which determined the neighbouring nodes in the network. The SOM size was chosen based on the amount of input data within a testing procedure since no statistical rule exists for optimal size determination. The input data space included 11 variables per country and a total of 283 observations (consisting of available secondary data for individual years for 45 countries). Data were not pooled per year or per country. The SOM model generated data clusters; therefore, the a priori position of an individual country did not influence the position of data for subsequent years for the same country. The SOM model was trained using MATLAB software by MathWorks (Massachusetts, USA) (2022).

In the second step, the addition of a third dimension comprising data on population wellbeing resulted in the three-dimensional positioning of countries (XYZ). The data on population wellbeing were derived from HDI values that had been translated into country rankings from 1 to 185 (best to worst). This ranking was based on the total global sample of countries but, since only 45 countries were included in our dataset, not all rankings are present in the analysis. The XYZ positioning evolved as follows: the SOM's two-dimensional position represents the XY plane, and population wellbeing is the Z dimension.

In the third step, we aimed to resolve the "black box problem" of neural networks by attempting to explain the position of a particular country in the wellbeing model. Therefore, we observed the association of each input variable of the SOM model within the wellbeing model. In this unusual methodological approach, the relationship to population wellbeing as identified in the final step is set independently from the learning process of the initial SOM model, which uses only the characteristics of the health system (categories of healthcare expenditure and healthcare capacity) and not population wellbeing data.

RESULTS

SOM clustering model

A SOM model was trained using the 11 variables of health system architecture as input data. *Figure 1* shows the resulting network, with the number of observations indicated for each winning node. Clustering neighbourhoods are apparent as areas of greater density and clear boundaries called "valleys" between the cluster areas.

The third dimension generates the wellbeing model

We added the third dimension to the SOM clustering model using an estimated polynomial model based on the following general model:

$$z = \sum_{i=1}^{n+1} p_i x^{n+1-i} + \sum_{j=1}^{m+1} q_j y^{n+1-j}$$

where $n+1$ and $m+1$ are the orders (number of coefficients to be fitted), and n and m are the degrees of the polynomial (highest power of the predictor variable). This methodological approach has the advantages of having reasonable flexibility for uncomplicated data and being linear, which simplifies the fitting process. Its disadvantages are that high-degree fits are potentially unstable and that, while such models can provide a good fit within the data range, they can diverge outside that range [34]. Therefore, we decided to limit the orders to three levels in the estimation process. The procedure for fitting polynomials uses the predictor values

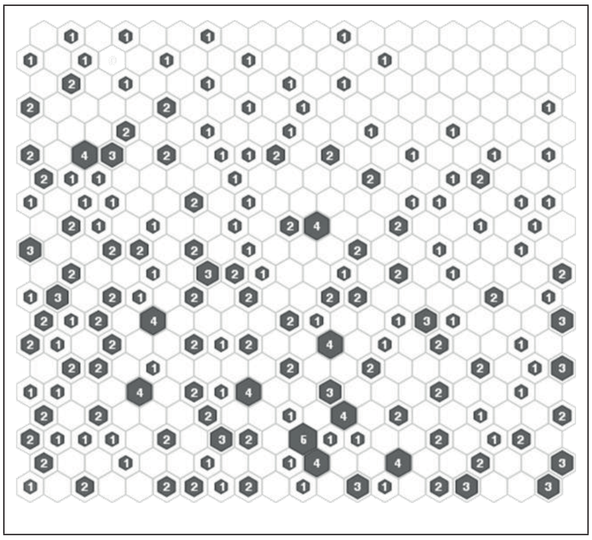
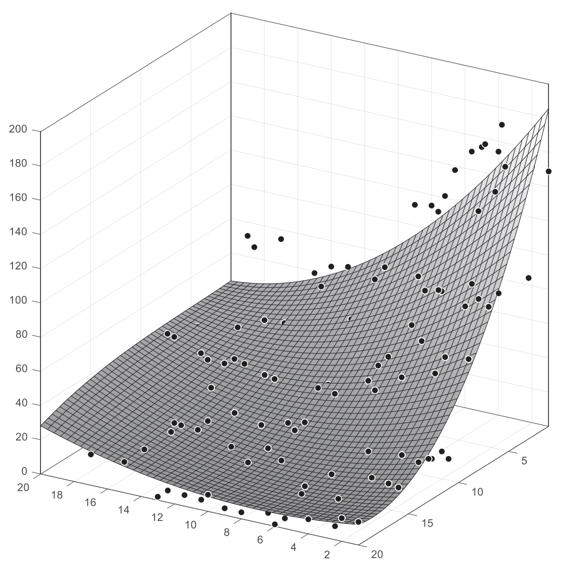


Figure 1
SOM model structure and number of hits.

as the basis for a matrix with very large values, which can result in scaling problems. To overcome this problem, we normalized the data by centring to a zero mean and scaling to unit standard deviation.

Figure 2 shows the SOM wellbeing model with unitless coordinates for the XY plane. These coordinates play a similar role to a principal component analysis. For each of the 283 observations, data on population wellbeing were added as a third dimension and marked by a dot. HDI data is given as the ranking. The best ranks (low values) in the HDI signify countries with higher population wellbeing and the worst ranks (high values) signify countries with lower population wellbeing. Next, a model estimation was designed, in which a planar surface represents the estimated relation between position in the SOM network and the population wellbeing level. The model estimation indicates areas of greater and lower population wellbeing, depending on the SOM positioning.



Note: the X- and Y-axes are unitless coordinates of the neuron position in the SOM model.
The Z-axis is the HDI ranking that reflects the wellbeing level.

Figure 2
Wellbeing model.

Model decomposition – solving the black box problem

We next explored the association of individual characteristics of health system architecture with the wellbeing model. Henceforth, the SOM clustering model is presented as an XY plane (as in *Figure 2*) and data on population wellbeing are presented in greyscale (rather than a third dimension). Areas with similar levels of population wellbeing form regions. Notably, areas with the highest levels of population wellbeing are darkest and are located in the top left corner. We next analysed the SOM model to determine whether countries with the same level of population wellbeing share similarities in the individual variables. *Figure 3* shows that having a small number of medical doctors, dentists or nurses/midwives is associated with low population wellbeing. However, in countries with a high level of population wellbeing, the number of each category of medical staff vary considerably. In countries with high population wellbeing, current health expenditure as a percentage of GDP is homogenously high, whereas in countries with low population wellbeing expenditure is low. In comparison, out-of-pocket expenditure as a percentage of current health expenditure is higher in countries with low population wellbeing than in those with high population wellbeing.

The model accuracy assessment

To critically evaluate the results, we assessed the accuracy of the wellbeing model. For this, we compared the predicted and true HDI values for each country using a standard ordinary least squares regression model *(Figure 4* and *Table 3)*. The results show that even though we did not model time series data, the adjusted R^2 value is extremely high (0.839), signifying that the model explains 84% of the total variation in HDI.

DISCUSSION

Two sets of findings were obtained. Firstly, the SOM clustering model revealed country clustering based on the characteristics of national health systems. A wellbeing model provided an empirical level of population wellbeing associated with each country cluster. However, the methodological approach did not provide sufficient evidence to indicate a causal relationship. Secondly, some unexpected patterns of association were observed between areas with different levels of population wellbeing and the average values of individual characteristics of health system architecture. For some characteristics, certain values were restricted to countries with specific levels of population wellbeing, whereas for others similar values were obtained for countries with low or high levels of population wellbe-

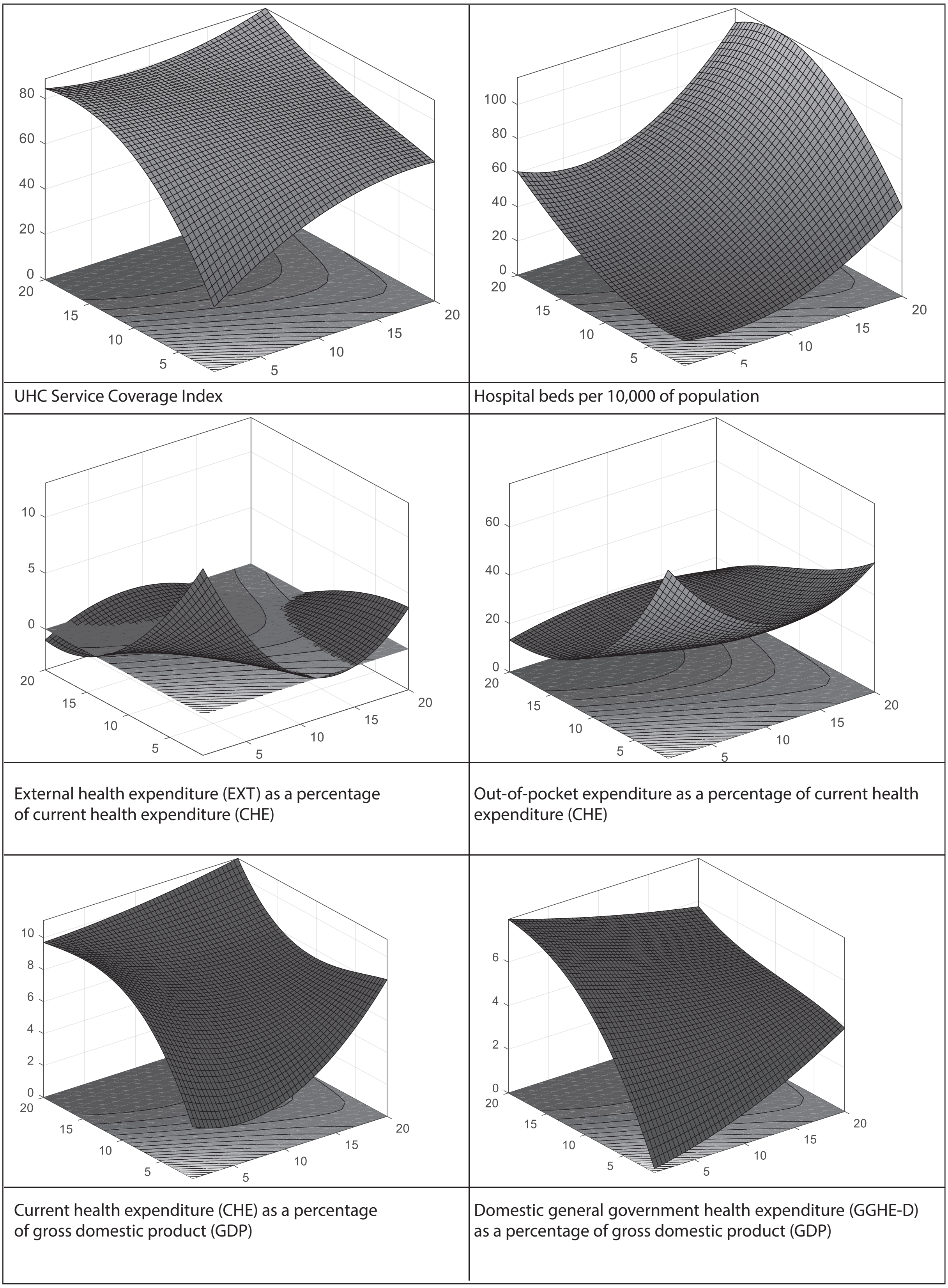


Figure 3
Associations of individual variables of health system architecture with population wellbeing.

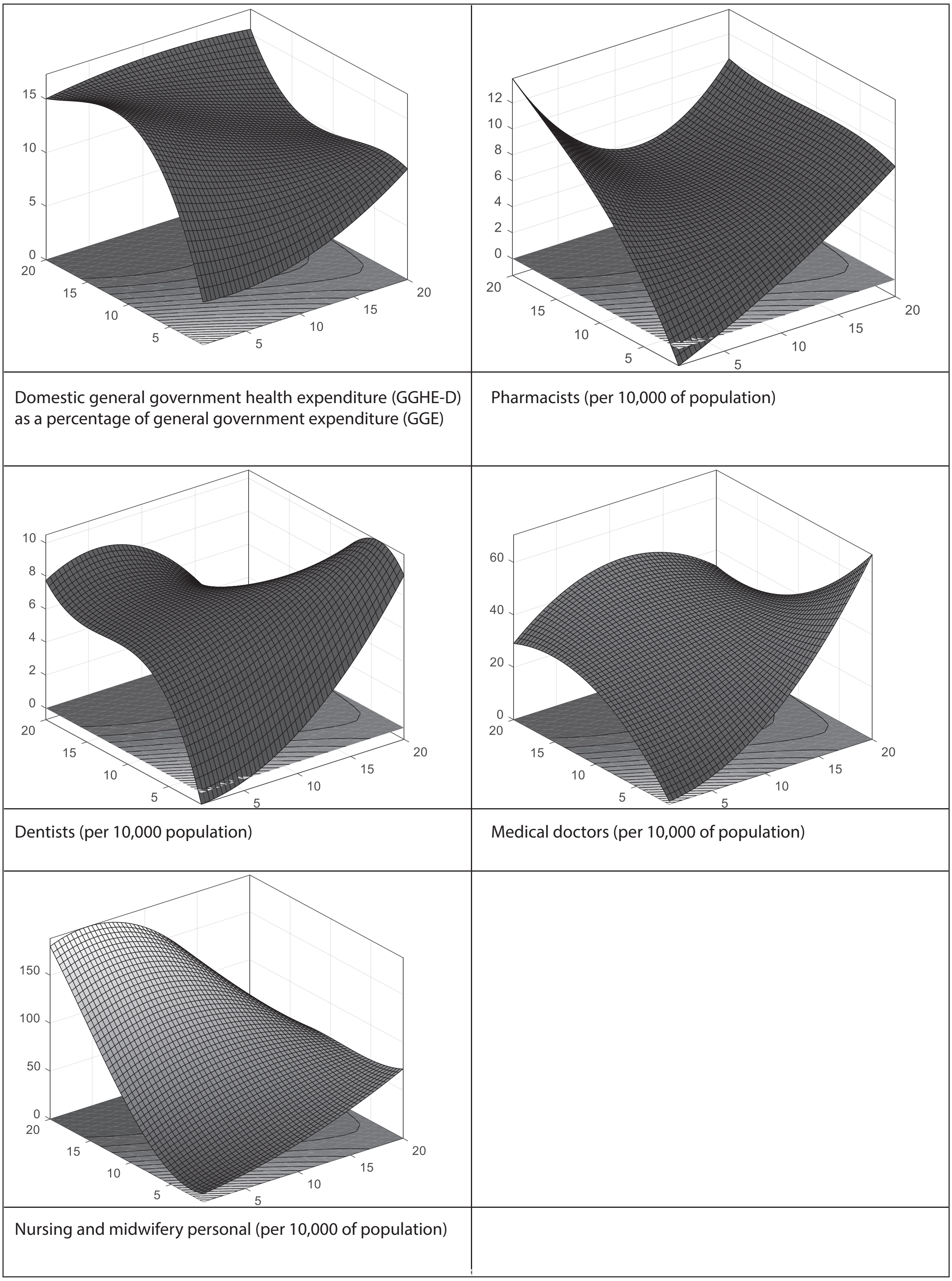


Figure 3

Note: the X and Y axes are unitless coordinates derived from the SOM model that reflect the position of neurons; the Z axis is the value of the individual variable. On the XY plane, the coloured areas reflect the projection of the forecast HDI value.

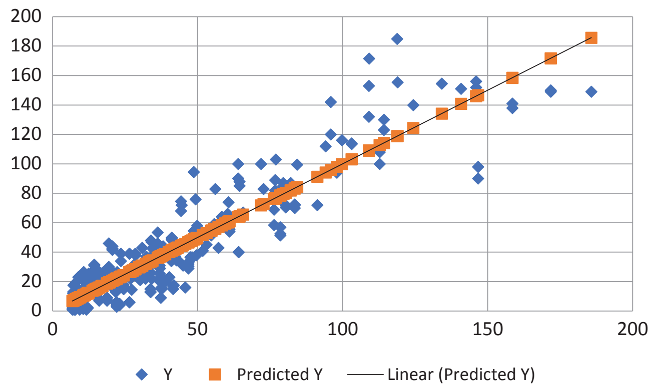


Figure 4
Accuracy assessment of the model.
Note: The X-axis is the model forecast and the Y-axis the country ranking. Wellbeing model.

ing. For example, analysis of the variable "Hospital beds per 10,000 population" *(Figure 3)* revealed that having a medium quantity of hospital beds is associated with both higher and lower levels of wellbeing. Furthermore, having an extremely high quantity of hospital beds is not a prerequisite for high population wellbeing, since the same level of wellbeing was found for countries with a medium quantity of hospital beds. In contrast, having a very low quantity of hospital beds was associated only with a low level of population wellbeing.

The limitations of the study should be considered when interpreting the results. Firstly, we measured wellbeing using the HDI, which simplifies human development by capturing some of its aspects and not others, such as human security and empowerment [13, 24]. However, the main limitation was the size of the database. The inclusion of more countries in the analysis would have resulted in greater robustness. However, the number of countries included in the study was determined by the availability of relevant data. Furthermore, for some countries, data were available for only a few years, resulting in a short time frame that is incompatible with the research aim. Therefore, when we excluded countries with too few years of available data, the number of countries was reduced from 185 to 45. To overcome the limitations of classical econometric methodology, we designed a tailored methodological approach. Firstly, the SOM clustering model benefits from properties of unsupervised learning of a neural network. Next, wellbeing information was strictly separated from other input data for country clustering. Therefore, the level of wellbeing was determined solely by independently assessed features of the healthcare sector.

The results indicate that different healthcare policy choices can achieve similar levels of population wellbeing. Therefore, once social agreement is reached on the desired level of population wellbeing, a broad set of policy options is available for specific health system characteristics. However, for other characteristics, the range of policy alternatives is much narrower. These findings may be useful for choosing national policy on designing health system architecture.

The findings have practical and managerial relevance: although the characteristics of a country's health system did not directly correspond to its development, it was possible to identify some patterns. Health systems were found to have different scopes and levels; however, countries in geographical proximity had similar health systems, suggesting that the countries also had a similar level of population wellbeing. Some countries without a large healthcare capacity could provide a reasonable

Table 3
Regression statistics

Regression statistics						
Multiple R	0.916169					
R Square	0.839365					
Adjusted R Square	0.838793					
Standard Error	15.60306					
Observations	283					
	Coefficients	**Standard Error**	**t Stat**	**P-value**	**Lower 95%**	**Upper 95%**
Intercept	-0.00586	1.467349	-0.00399	0.996818	-2.89425	2.882534
X variable 1	1.000031	0.026098	38.31852	1.4E-113	0.948659	1.051403

or good level of population wellbeing, suggesting a complex scenario in which the policy mix needs to be optimized in some countries. In other words, providing resources to the health system is not guaranteed to increase population wellbeing. Therefore, future research should focus on finding ways to achieve the maximum level of population wellbeing at the minimum cost to the health systems. The findings suggest that two levels of analysis are important: firstly, the analysis and comparison of countries within a certain group or cluster with similar health system characteristics and levels of population wellbeing; and secondly, an in-depth analysis of a country' s strengths, weaknesses, opportunities and threats based on micro- and sectoral-level data.

CONCLUSIONS

This study presents empirical findings that are important for science, health policy, society and health practice. A methodological approach based on neural networks was applied to secondary data from a large sample of countries in order to study the evolution of health systems in terms of country specificity and level of population wellbeing.

It contributes original and novel empirical results obtained from a large sample of country data on health system characteristics for selected years. We measured health system development based on its financial and healthcare capacity characteristics, as well as the level of population wellbeing. We assessed associations between these characteristics in country groupings but did not determine causality. The findings provide empirical evidence that similar levels of population wellbeing can be achieved in health systems with different characteristics based on differing policy options. The investigation confirmed both research questions: RQ1, that the specific characteristics national health system are reflected in population wellbeing; and RQ2, that similar levels of population wellbeing can be achieved with different health system architectures.

Therefore, it is crucial to increase not only expenditure and capacity in the healthcare sector but also the efficiency of the health system. Empirical evidence for a large number of countries suggests that different levels of health system performance can be achieved in different ways. Some countries with fewer resources were able to achieve high levels of population wellbeing, and other with more resources had achieved modest or low levels of population wellbeing. This suggests that resource availability cannot be the main constraint to achieving population wellbeing. If resources are used inefficiently or there is a lack of competition or bottlenecks in the health system, more resources do not necessary improve population wellbeing. It is important to understand how the health system functions and its constraints. This is impossible to achieve without comparisons of health systems in both neighbouring countries and worldwide, which is a crucial contribution of this study.

During the COVID-19 pandemic and associated healthcare crisis, expenditure on health system characteristics and capacities was raised in many countries. However, whether increased healthcare expenditure led to improved population wellbeing is a question for future research. Other suggestions for future research include an in-depth investigation of individual health systems based on an analysis of time series data or of country clusters to identify the drivers of (in)efficiencies over time and between countries.

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Conflict of interest statement

The Authors declare no conflict of interest.

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