

A Systematic Approach to Identify Health System Resilience Indicators Using Artificial Neural Network Algorithm

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Abstract—According to the World Health Organization (WHO), a health system comprises all organizations, people, and actions that aim to promote, restore, or maintain health[1]. Health systems perform multiple functions in society not only delivering healthcare services and other interventions aimed at maintaining or improving health. They serve multiple societal functions beyond merely delivering healthcare services, but also adapting to risks, disasters, and unpredictable events to maintain functionality. Health system resilience, therefore, refers to the system's capacity to adapt and return to previous performance levels as quickly as possible after such disruptions. The WHO has created a model called Six Building Blocks to measure the health system's resilience. This study aims to assign indicators obtained from a comprehensive literature review to the blocks established by the World Health. The study uses an Artificial Neural Network (ANN) algorithm to analyze data from 35 Organisation for Economic Co-Operation and Development (OECD) countries from 2020 to 2022. ANN is used to assess the varied relevance or weights of each building block's contribution to health system resilience, providing detailed knowledge of how different components impact overall health system performance during crises. As a consequence of this study, policymakers may identify which healthcare building block and accompanying indicator should be prioritized for investment in preparation for future pandemics. The findings suggest which characteristics are most important for increasing health system resilience during public health emergencies.

Keywords— Health System Resilience, Artificial Neural Network, System Engineering, Resilience Engineering

I. INTRODUCTION

Health system resilience refers to the capacity of the healthcare system to rapidly adapt to unforeseen disasters and risky situations, while expeditiously restoring its previous level of operational performance in the shortest possible time frame[2]. The operations of health systems have come under pressure from disruptive events such as pandemics, natural disasters, economic crises, man-made disasters, and many other similar unexpected and inevitable events[2]. Health system resilience is a concept that has been discussed since the early 2000s. The World Health Organization (WHO) has identified six building blocks constituting a health system in its Health Systems Framework (World Health Organization., 2007). In this framework that is shown in Figure 1 health system resilience is defined with six building blocks: (1) Leadership and Governance; (2) Information; (3) Health Workforce; (4) Financing; (5) Medical Products; and (6) Service Delivery. This framework aimed to identify the components of a resilient healthcare system. The WHO Building Blocks framework has been widely used in health systems research and has arguably become the framework most often used to describe a health system in international forums [3], [4].

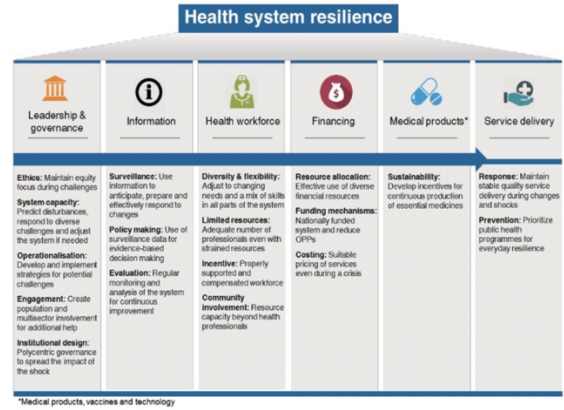


Figure 1: Six building blocks for health system resilience[5]

However, analysis of health system resilience studies is challenging since the factors do not numerically indicate their significance in the system. Along the same lines, as others have noted, the literature is relatively silent on the interactions between the six building blocks in the framework, and, as a result, it remains rather static [4], [6]. With the advent of the COVID-19 pandemic, research and assessments in this field have gained increasing importance. The COVID-19 pandemic is the most severe global health emergency since the 1918–19 influenza [7]. The COVID-19 pandemic, which originated in the late months of 2019, resulted in nearly 7 million deaths. As of May 5, 2023, the WHO COVID-19 Emergency Committee announced that while the pandemic has not ended, the global emergency it caused has currently come to a close.

This study uses machine learning to measure the weights of the aforementioned WHO's Six Building Blocks. Attributes that may impact the health system's resilience were determined and matched with the relevant block using information obtained from the literature. After assigning these measurable attributes to the six building blocks, an Artificial Neural Network algorithm is employed for analysis. This algorithm is used to measure the resilience of a health system using general health data and COVID-19 pandemic-related data from Turkey and 35 other OECD countries.

II. LITERATURE REVIEW

The literature review has been conducted gradually; firstly, understanding the concept of health system resilience, the framework of health system resilience, and resilience measurement models. Finally, specific emphasis is given to the recent literature about the machine learning approaches to evaluate health systems.

In a study conducted by Doupe et al, researchers studying healthcare outcomes use new machine learning techniques

because making predictions has become more important lately. By combining causal studies with predictions, our understanding can be improved. With this work, they want to reduce the obstacles to applying machine learning techniques[8]. Turenne et al, defined that “Health system resilience” is still a very confusing topic. As a result of the evaluation poured into this study, the idea of health system resilience has not yet reached conceptual maturity, and the various conceptual frameworks used by academics remain unreliable and not widely accepted [9]. Rustam et al, the ES algorithm gave a better result by training 66 data sets than the other three algorithms. Outputs were compared with real data, and the results were found to be close to each other [10]. In the study of Gürfidan&Ersoy et al, heart diseases were classified using machine learning. Trainings were conducted, and an 83% success rate was achieved as the highest value. In future studies, it aims to increase the final success rate to over 90%[11]. Olivato et al. concluded their study with experimental results demonstrating strong performance in classifying patients based on their length of stay. Their best model achieved an F1 score and ROC-AUC value of 0.76, indicating effective differentiation between long and short stays [12]. It is shown that applying the WOC approach leads to a noticeable improvement in performance. An artificial neural network (ANN) has been successfully used to solve highly complex problems within the physical sciences and, as of late, by scholars in organizational research as a digital tool enabling faster processes of data collection and processing[13], [14]. As practical and flexible modeling tools, ANN can generalize pattern information to new data, tolerate noisy inputs, and produce reliable and reasonable estimates [13][14].

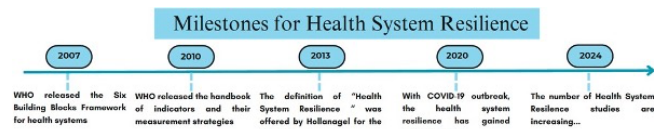


Figure 2: Timeline of the health system resilience[2]

In this literature review, the evolution of the topic of health systems resilience was also examined. As shown in Figure 2 in 2007, the concept of resilience in health systems was discussed in a report published by the World Health Organization (WHO), and at the beginning of the COVID-19 pandemic in 2020 health systems resilience topic gained more attention. Resilience is measured by the quickest return of the system to its pre-disaster operating capacity during challenging situations or unexpected problems. Many different models or frameworks can be used to measure the durability of the system. In the six building blocks published by the WHO, was concluded that the weights of all blocks were considered equal. The project aims to determine the contributions of the six building blocks to the resilience of the health system by using an artificial neural network algorithm. Thus, it is determined which parameters policymakers should focus on for health system resilience.

III. METHODOLOGY

ANN technique was used in this study to assess the health system's resilience. This methodology measures the six building blocks of health system resilience by integrating a significant number of variables. After a thorough analysis of

the literature, the indicators were carefully chosen and placed in the appropriate building blocks to form a comprehensive and strong assessment framework. The ANN algorithm was chosen for its ability to handle complex, non-linear relationships between these indicators and the overall health system resilience. To measure six building blocks, the attributes obtained from the literature study were added to the appropriate blocks, and Figure 3 was obtained.

Attributes for each Building Block		
Leadership & Governance - Risk Communication - Government Effectiveness	Information - Information System for Pandemic - Countrywide e-Health System	Health Workforce - Number of doctors per 1000 population - Number of nurses per 1000 population
Financing - Health Expenditure per Capita in US\$ - Health Expenditure as % of GDP - Health Insurance Coverage % of Total Population	Medical Products Number of adult ICU beds per 100,000 Population	Service Delivery - Number of Hospitals per Million Population - Number of Hospital Beds per Million Population

* M. Edwin S, von Schreeb J, Saulnier DD. Health System Resilience: What Are We Talking About? A Scoping Review Mapping Characteristics and Keywords. Int J Health Policy Manag. 2020 Jan 1;9(1):6-16. doi: 10.15171/ijhpm.2019.71. PMID: 31902190; PMCID: PMC6943300.

Figure 3: Attributes for each Building Block

The ANN was trained on retrospective data created from online sources. Firstly, at least one attribute for each block and thirteen attributes were chosen to evaluate the weights of the six building blocks. To create the artificial neural network, the number of nodes, number of layers, and activation functions were determined. The data set was divided into training and test sets. After the features and output, that is, the target variable, were determined, training continued for the number of epochs, and the performance of the model was measured. The trained ANN model was then validated using a separate dataset to assess its accuracy and reliability. The Mean Squared Error (MSE) value was one common statistic used to assess the model's effectiveness. Finally, the weights assigned to each block were determined. The outcomes showed how well the ANN model predicted health system resilience, providing significant insights into the strengths and weaknesses of various health systems.

A. Data Collection

The dataset was obtained through a structured, three-stage process to ensure completeness and accuracy. Initially, the primary source of data was the “OECD Health Statistics” website, which provided a substantial portion of the required information. However, for data points that were missing, additional information was sourced from the “Our World in Data” platform, which offers a wide range of global health statistics. In cases where data remained unavailable after consulting these two sources, the third stage involved retrieving the necessary information directly from the “Official websites of national health ministries” of the respective countries. This multi-step approach ensured the dataset was as comprehensive and reliable as possible, incorporating official statistics from multiple authoritative sources. The dataset includes information from January 1, 2020, to December 31, 2022. There are thirty-four countries

from seven continents in the dataset, but there are missing data in some rows and columns, these data are eliminated with the code of the algorithm. To define the six building blocks, thirteen parameters have been evaluated. Countries selected from mainly OECD countries and, at least one from each region.

B. Data Preprocessing

Initially, the data was obtained in daily values, however, the values for each attribute are not changing daily. For example, the number of the doctor is not changing daily, as a result, the daily values were converted to yearly values by choosing the initial values for each year. In the data set each row represents a different country's data from three years and each column corresponds to one of the 13 selected indicators used to measure health system resilience. The selected attributes and their citations are shown in Table 1. The steps that in shown in were Figure 4 applied gradually.

Table 1: Definitions of attributes

Attribute	Definition
1. Location	The name of the country
2. Year	The year of the selected data for the country
3.Global Health Security Index	The global health security index of the selected country
4.Risk Communication	The risk communication level of selected country
5.Government Effectiveness	The government effectiveness level of selected country
6.Information System for Pandemic	Was there an information system during COVID-19?
7.Countrywide-Health System	Is there an e-Health system in the selected country?
8.Number of doctors per 1000 population	The number of doctors in selected country
9.Number of Nurses per 1000 population	The number of nursing personnel in selected country
10.Health Expenditure per Capita in US\$	The amount of current health expenditure for selected country
11.Current Healthcare Expenditure as % of GDP	Healthcare expenditure in current GDP as % for selected country
12.Health Insurance Coverage % of Total Population	Insurance coverage in total population for selected country
13. Number of adult ICU beds per 100,000 population	The number of ICU beds for selected country
14. Number of Hospitals per Million Population	The number of hospitals for selected country
15. Number of Hospital Beds per Million Population	The number of hospital beds for selected country
10.Health Expenditure per Capita in US\$	The amount of current health expenditure for selected country
11.Current Healthcare Expenditure as % of GDP	Healthcare expenditure in current GDP as % for selected country
12. Health Insurance Coverage % of Total Population	Insurance coverage in total population for selected country
13. Number of adult ICU beds per 100,000 population	The number of ICU beds for selected country



Figure 4: Workflow of the model

C. Artificial Neural Network

ANN can have single or multiple layers [13] and consist of processing units (nodes or neurons) that are interconnected by a set of adjustable weights that allow signals to travel through the network in parallel and consecutively[15], [16]. Generally, ANN can be divided into three layers of neurons: input (receives information), hidden (responsible for extracting patterns and performing most of the internal processing), and output (produces and presents final network outputs). As the complexity and uncertainty with the data (that describes the decision situation) increase, the capabilities of the model (that represents the situation) should also increase, so that highly nonlinear relationships among the variables can also be captured[17]. So ANN is proper to get weight and eventually help the policymakers. In this study, a 3-layer neural network is to get weights.

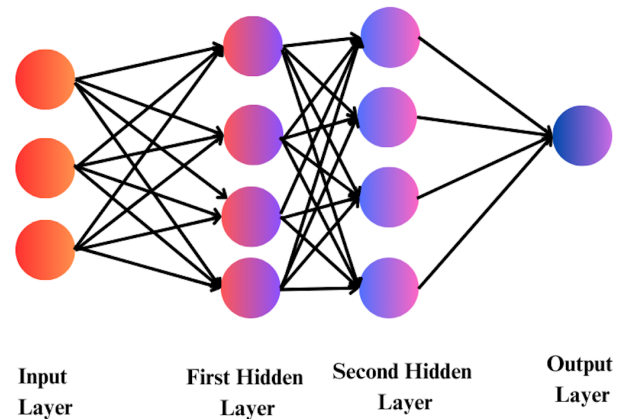


Figure 5: 3-Layer Neural Network

IV. RESULTS

As a result, the ANN algorithm suggests that “Health expenditure as of GDP”, “Government Effectiveness”, and “Number of adult ICU beds per 100,000” are the most important attributes than the others.

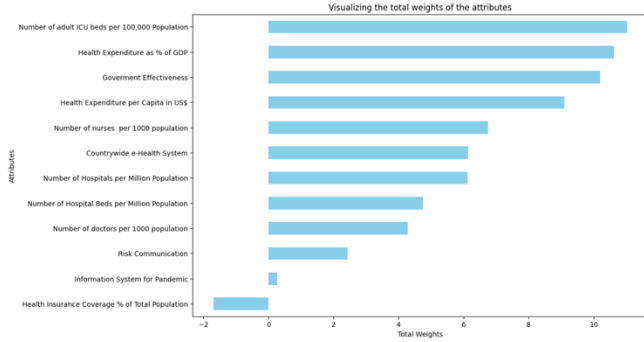


Figure 6: Visualizing the weights of each attribute

Gradually, the number of adult ICU beds per 100,000 population is revealed to be the highest weighted attribute, implying that the availability of intensive care unit beds is a major factor of health system capacity. Secondly, Health Expenditure, as a percentage of GDP, indicates the importance of how much a country allocates towards the health system relative to its economic output. This is a strong measure of a nation’s commitment to public health investment. “Government Effectiveness” also plays a key role since the effectiveness is directly related to managing the health system and the reliability of the government. At the lower end of the weighting, Risk communication and information systems for pandemic attributes are important however they are given less emphasis in the analysis. This suggests that although these factors are beneficial, they may not influence health system effectiveness as directly or significantly as the more heavily weighted attributes.

The ideal Mean Squared Error (MSE) value should be as close to zero as possible, indicating minimal prediction errors and high accuracy of the model, and in this study, the average MSE is 0.001166. Figure 6, visualizes the total weights of the attributes, highlighting their relative importance in the overall evaluation. Each bar represents the weight of a specific attribute, demonstrating the factors that contribute most significantly to the system.

A. Leadership and Governance

The COVID-19 pandemic that began at the end of 2019 demonstrated how important it is to manage healthcare systems, develop policies, and take appropriate steps for the resilience of health systems. Leadership and governance form the foundation for building a resilient health system. The government’s decision-making institutions and the Ministry of Health are responsible for establishing a fair, high-quality, and sustainable health system. These stakeholders in the health system encompass policies and processes. By formulating strategies and developing effective and timely solutions tailored to the country’s conditions, health systems can be defined as resilient. The necessary planning, which affects all citizens of the country and is connected to the population in addition to other parameters, is considered suitable for evaluation under the title of the “Risk Communication”, and “Government Effectiveness”

parameters within the six building blocks, specifically under the leadership and governance category [5].

B. Information

Another title that will be used to measure the resilience of the health system is information. While the management of health systems ensures their preparedness for unexpected situations, sharing this management or the conducted process with the public makes the system understandable. In addition to the government’s ability to adapt quickly to the pandemic process, the public must understand the importance of this process and be able to adapt to it for the system to function effectively according to the needs. Informing the public through applications or press conferences provides an opportunity to convey the ongoing process to the public. The existence or absence of an app or website created by governments to inform the public has been considered so, “Having an information system during the COVID-19 Pandemic” and “Countrywide e-health system” have been chosen. Through these systems, the public can view continuously updated data on cases, deaths, and vaccination rates. The aim is not to instill fear in the public, but rather to present the process to the public with all transparency [18].

C. Health Workforce

To achieve a resilient health system, quality care must be provided to patients, which is ensured through an effective health workforce. During the COVID-19 pandemic, the uninterrupted work of healthcare workers was crucial for the implementation of treatments following the protocols defined by the World Health Organization and national health ministries. In some countries, an additional workforce was mobilized to alleviate the pressure on the healthcare workforce and ensure the continuity of health system services. The aim was to reduce the patient-to-doctor ratio and workload. Additionally, positive changes were made in working hours, regulations, salaries, and the rights granted to healthcare workers to provide them with some support during this challenging period. To measure the aspect of the health system’s resilience related to the health workforce, the parameters “Number of Doctors” and “Number of Nurses” were used. This measure allows for the assessment of the number of doctors continuing to work under pressure, thus monitoring the continuity of patients’ access to treatment [19].

D. Financing

Financing is another important component of the health system’s resilience. During unexpected events like a pandemic that significantly impact the healthcare system, securing initial funding sources and maintaining financial resources throughout the process is crucial. Governments typically allocate budgets for healthcare services on an annual basis, with relatively consistent funding each year. However, in such situations, increasing investments in the healthcare budget allows for more effective implementation of measures within the health system. It is expected that the government will increase healthcare spending during these periods to ensure that all citizens can access healthcare services. The parameter “Current Health Expenditure in US Dollar”, “Health Expenditure as % of GDP” and “Health Insurance Coverage % of Total Population” were used to measure this

aspect, and for ease of comparison, the evaluation is based solely on the value in US dollars [20].

E. Medical Products

Governments should support the resilience of healthcare systems with innovative technologies and solutions during unexpected situations. In cases of system overload, medical product shortages, or when the prices of products exceed the standard, governments should provide their citizens with free access to necessary technologies or treatments. Therefore, the accessibility of medical products supports the resilience of the healthcare system. For this reason, the parameter "Number of adult ICU beds per 100,000 Population" was used to evaluate the medical products category.

F. Service Delivery

In situations like a pandemic, where healthcare systems are directly affected, healthcare services must continue uninterrupted and adapt to new circumstances. When healthcare systems face intense pressures, efforts should be made to enhance capabilities. For the healthcare system to be considered resilient, it is expected that every patient has equitable access to treatment. The "Number of Hospitals per Million Population" and "Number of Hospital Beds per Million Population" attributes have been evaluated to assess service delivery [2], [21].

	Total Weight
Risk Communication	2.430502
Government Effectiveness	10.196510
Information System for Pandemic	0.273441
Countrywide e-Health System	6.138495
Number of doctors per 1000 population	4.281959
Number of nurses per 1000 population	6.759452
Health Expenditure per Capita in US\$	9.097276
Health Expenditure as % of GDP	10.623952
Health Insurance Coverage % of Total Population	-1.694457
Number of adult ICU beds per 100,000 Population	11.025047
Number of Hospitals per Million Population	6.125252
Number of Hospital Beds per Million Population	4.755324

Figure 7: Total weight values for each attribute

V. DISCUSSION

An artificial neural network (ANN) was utilized in this study to ascertain the weights of six building blocks for assessing the resilience of the health system. The ANN model successfully allocated weights to several attributes, producing a mean squared error that was almost zero, a sign of the model's high prediction accuracy. The attributes with the highest degree of influence were Government Effectiveness (10.196510), Health Expenditure as a proportion of GDP (10.623952), and Number of adult ICU beds per 100,000 population (11.025047).

A negative weight was assigned to factors such as the proportion of the population having health insurance coverage (-1.694457), indicating a negative correlation with the resilience score. These results demonstrate the complexity of health system resilience and the value of a comprehensive strategy that includes sufficient critical care infrastructure, appropriate finance for healthcare, and efficient governance.

VI. CONCLUSION

To assess the resilience of health systems, this study effectively used an Artificial Neural Network (ANN) to calculate the weights of the six WHO-defined building blocks. The low mean squared error of the ANN model suggests a high degree of accuracy in evaluating the resilience of the health system. Through the examination of data from 34 nations on many continents between 2020 and 2022, the research offers a comprehensive viewpoint on the resilience of health systems. The research is enhanced by the inclusion of COVID-19-related and general health data, which provides insights into how many factors interact to promote resilience. This study emphasizes how crucial it is to develop the entire health system, with a focus on critical care capacity, enough financial resources, and efficient governance. The work makes a substantial contribution to the discipline with its creative application of machine learning to measure the significance of many elements of the health system. It offers a data-driven method for comprehending and improving the resilience of the health system. Future studies should examine the interdependencies between the building blocks in greater detail and create focused strategies to increase resilience so that health systems are prepared to quickly adjust to and recover from crises in the future.

Using the weights derived from this research, policymakers may pinpoint crucial areas that need to be improved to increase the resilience of their health systems. They can increase the capability of their healthcare systems by implementing focused interventions by concentrating on these important determinants. As a result, these initiatives will better position their nations to handle and recover from any future health emergencies.

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