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Machine Learning for Predicting Healthcare Policy Outcomes: Utilizing Machine Learning to Forecast the Outcomes of Proposed Healthcare Policies on Population Health and Economic Indicators

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ABSTRACT

This study aims to explore the relationship between healthcare costs, growth rate, and health care in various societies around the world. The paper, therefore, adopts statistical analysis to analyze the variables; Health Expenditure as a percentage of GDP, GDP Growth Rate, Healthcare Access, and GDP per Capita on a cross-sectional sample that encompasses multiple countries and years. The study establishes a direct relationship between health expenditure on the one hand, and the GDP growth rates on the other hand, so it shows that high health expenditure is an engine of better economic development. Further, the assessment brings out the effect of GDP per Capita in determining health care accessibility, thus, pointing toward inequality in the provision of health care according to the income level of the people in the country. Policy implications focus on the need to achieve strategic healthcare financing congruent with the set economic policies to guarantee healthcare service delivery for everyone. The study is useful for users interested in understanding the complex factors that impact the efficiency of healthcare systems and subsequent sustainable socioeconomic advancement in the world.

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Introduction

Healthcare policy is an essential component of social welfare platforms, and it affects the health of the nations as well as the economic status. Policy formulation calls for extensive knowledge of how the intended policies will affect all aspects and the general well-being of health. Modern ML and informational analysis provide valuable tools for precise and accurate predictions of the possible consequences of healthcare policies for researchers and policymakers.

Background

In the context of analyzing the impact of political changes on the field of healthcare policy, it should be noted that the traditional approach previously used was the statistical modelling of policy results and the use of experts' forecasts of policy influence. Although these methods yielded useful information, they had limitations in forecasting because the relationship of many factors was intertwined in healthcare systems [1]. Machine learning, on the other hand, is a novel method that can analyze huge amounts of data and pick up complex and hard-to-spot trends and relationships. Some defining features include the capability in specific tasks like learning from data, recognition of patterns, modelling, and optimization which makes the application of machine learning very suitable in healthcare policy analysis [2]. ML entails the use of past policy data with the appropriate health and economic statistics whereby training of models produces trends that help in arriving at the best decisions by the policymakers. These decisions are vital not only to ensure the efficient use of resources but also to avoid or at least minimize the risks of having adverse side effects of change of any policy.

Aim and Objectives

Aim

This study aims to develop a machine learning model that will estimate the impacts of recommended healthcare policies on population health and economic factors.

The Objectives are Structured as Follows

- **To analyze historical healthcare policy data:** In this objective, raw data sets containing historical healthcare policies, demographics, and requisite economic indices should be collected and assessed.
- **To develop predictive models:** Using machine learning techniques, design models that predict the effects of new health care policies health indicators such as incidence and mortality of diseases, and health facility access.
- **To assess economic implications:** Assess the economic consequences of the proposed changes within the sphere of healthcare, such as changes in healthcare spending, GDP rate, and proportion of working places in the sphere of healthcare.
- **To provide actionable insights:** Transform the model output into policy-relevant insights for policymakers, recommendations of policy changes or interventions based on the predicted values.

Literature Review

Integration of Big Data Analytics in Healthcare Policy

Big data analytics in synergy with ML approaches has unlocked new horizons in the analysis of healthcare policy. Large datasets include traditional and emerging data types including electronic health records, claims data, sociodemographic data, and population health surveys. Often, these huge samples are valuable for investigating intricate dependencies between various components of healthcare organizations and estimating the possible consequences of policy changes [3]. Supervised and unsupervised machine learning planning algorithms have proven influential in analyzing Big Data to inform healthcare policies. Using revelation and classification learning methods, the probable health and economic status can be estimated from earlier data regularity. The clustering and association techniques contribute to the discovery of underlying patterns and structures in the data, which enrich the understanding of policy-making and guide the strategies used in policy implementation.

Big data analytics in healthcare policy does not stop at previsions, but it also encompasses monitoring, trending, and the efforts for personalized medicine. Real-time data processing in health care is useful for policymakers to analyze trends in the sector in real-time and adapt the polices according to the emerging health issues or demographic demands of the population [4]. Furthermore, demographic and clinical behavioral analysis about populations allows containing necessary intercessions concerning healthcare availability and quality, as well as resources usage.

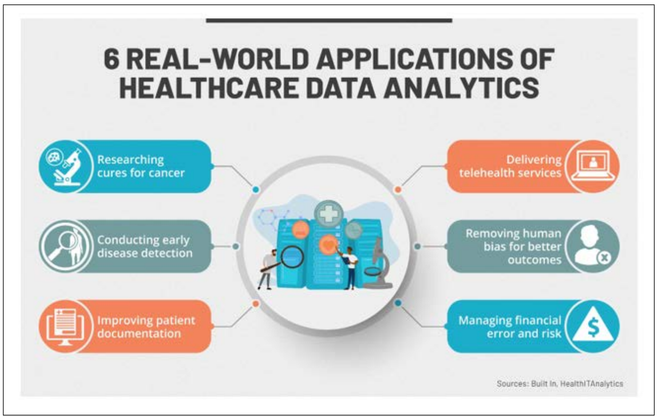

Figure 1: Benefits of Data Analytics in Healthcare

However, the following challenges are evident and continue to hinder the application of big data analytics in the formulation of healthcare policies. Similar to any form of data, big data can also have problems with data quality, communication obstacles between dissimilar types of data, and privacy and security concerns, which call for effective standard regulations and ethical standards in big data management [5]. Moreover, the interpretability of learnt models is still an open issue when it comes to maintaining the transparency of the decision-making procedures as well as gaining the confidence of the stakeholders. There are vast opportunities when big data analysis and machine learning are used in support of evidence-based reforming of this sphere [6]. Through the use of large and various datasets and data analysis as well as the help of data scientists, policymakers can strongly contribute to the advancements of population health, the distribution of healthcare and equal access to it and the successful management of health resources.

Policy Evaluation Frameworks and Methodologies

Policy evaluation relevant to healthcare must be anchored on sound paradigms and approaches in order to determine the effect of implemented policies on the health status of the populace as well as fiscal indices. Conventional methods like cost-benefit analysis and randomized controlled trials have remained the cornerstone of healthcare policies' valuation [7]. However, as a result of machine learning (ML), there are new approaches to use for performance evaluation that support the conventional ones. Machine learning makes it possible to develop models and digital simulations for the evaluation of policy impact on diverse interrelated associations in the sphere of healthcare [7]. In contrast to the past approaches in statistical analysis and modelling that are usually based on some linear approximations, the ML models can consider datasets of massive size and multiple dimensions to recognize interactions in calculated nonlinear functions. This capability is important in assessing the effects of policies on different communities within the population and the healthcare systems.

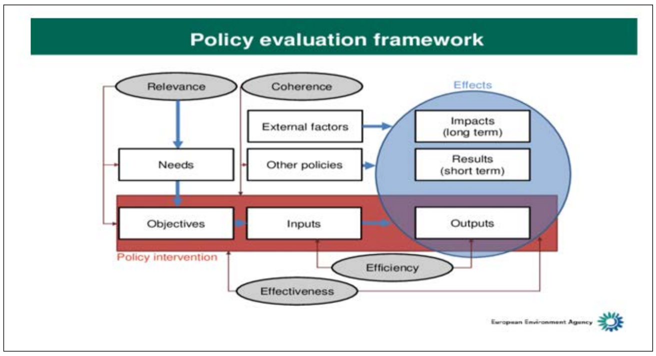

Figure 2: Policy Evaluation Framework and its Relationship with Evaluation

Another aspect where they have the upper hand in applying ML in policy evaluation is that it handles variables from multiple datasets such as EHR, claims, SDOH, and other contextual factors. These multiple data sources can then be combined for a holistic examination of various policies' effects on specific population health indicators such as disease incidence, mortality, and usage of health services [8]. In addition, it helps in the determination of the causal relations and predictive models needed for developing sound policies with specific recommendations for a given population's needs. Evaluation frameworks based on Machine Learning also solve the issues related to realistic variability and complexity in the HC environment [9]. Modern big data analysis tools include NLP, SA, and PM and their application can help policymakers to get a detailed understanding of the socio-economic factors that influence health and the viability of interventions in the long term.

Nevertheless, there are certain difficulties arising from the use of ML in policy assessment. Proper data protection, explainability of the algorithms and mitigation of biases in data gathering and in model results are important concerns. However, applying ML to a policy decision may also require some level of synergy between policymakers, healthcare practitioners, and data analysts to make the findings meaningful in policy intervention and regime. Policy evaluation frameworks based on machine learning are the shift of the paradigm in the field of evidence-based policymaking in healthcare. This way, applying advanced analytics and various data types, ML helps policymakers make decisions that would improve the population's health and increase the efficiency of the health care system, also addressing the issue of equality in access to needed health care services.

Impact Assessment Metrics

Monitoring and evaluation indicators help in determining the extent to which health policies have been effective and efficient in delivering positive results to the society hence assisting the policymakers in their decision-making processes. Conventional methods of assessing the relative efficiency of treatments and projects have been cost–benefit ratios, and quality-adjusted life years (QALYs). The integration of machine learning (ML) brings about different dimensions of policy impacts over general and dynamic datasets [10]. Analytical assessments based on ML methods use sophisticated data analysis to identify possible ripple effects that may be posed by any politico-economic policy decisions on population demography and health, as well as economic returns. These techniques allow the ability to look at various options and predict the outcome should a policymaker want to direct activities in a certain way the results will be. Being based on the analysis of historical data and learning patterns of healthcare consumption, the presence of diseases, and changes in the economic situation, ML models allow an understanding of the effects of policies that may remain imperceptible using other indicators.

Figure 3: Impact Assessment Metrics

Another advantage of applying ML in impact assessment is the consideration of interrelations and interdependencies within the healthcare systems. Presently, it is possible to develop ML algorithms that could produce and analyze big datasets that contain multiple essential variables such as SDoH, genetics, and the environment. This way, the approach helps them to estimate the effect of policies on subpopulations and to evaluate the equity results in relation to different categories of population. Also, ML enables timely appropriate control monitoring and real-time policy tuning because it analyzes data streams as they arrive and updates the models. This dynamic capability increases the firm's ability to respond to new trends in health and also the ability to actively respond to policies in executing strategies [11]. However, the inclusion of Metrics for impact assessment through the utilization of ML in healthcare policies has some limitations. Data integrity of model inputs and outputs, possible biases in data gathering procedures and the models themselves, and explaining the model results to all stakeholders are the core concerns here. Further, issues of data privacy, data sharing, and data ownership must be addressed in ways that adhere to patient rights, and sensitivity to issues of fairness to decrease skepticism towards the use of data in developing policies. The employment of ML in impact assessment indicators can be seen as a shift in the process of evaluating healthcare policies [12]. Through the use of large-scale analysis and forecasting techniques, it is possible to conclude that with the help of precise distribution of resources in healthcare, management of health risks, and implementation of the necessary conditions for delivering high-quality services, governments can ensure the development of effective healthcare systems that will be beneficial for as many people as possible.

Challenges and Future Directions

The application of ML in healthcare policy analysis brings positive implications for the future, but there are some critical issues that remain to be discussed intensively in further studies.

Challenges

Data Quality and Integration

Healthcare data is another critical issue as it must be of high quality, consistent, and interoperable. The EHR data are mainly generated in the clinical setting and collected in electronic format while administrative claims data are mostly structured claims submitted to payers and public health databases come in various forms and formats. Solving these issues needs sound data management frameworks and the ability of different healthcare systems to communicate with each other.

Algorithmic Bias and Fairness

Even though the choice of feature vectors is obviously crucial for the correctness of the final result, the problem of how to construct a fair classifier by means of training a confirmatory function from a set of features was shown to be mostly unsolvable, because the resulting classifier remains biased by discriminations built into the training data with respect to any grouping of individuals by demographic characteristics [13]. Reducing bias in algorithms involves proper data pre-processing, selection of the right algorithms for designing, as well as regular assessments in order to check whether the policies they recommend are fair and unbiased or not. Also, it is necessary to explain steps that have been taken to create a model, select a model, or make a decision, this will help to gain the trust of other interested parties and reduce the rating of unfairness.

Ethical and Privacy Concerns

Thus, the employers' utilization of the depicted sensitive healthcare data involves ethical concerns such as patient privacy, informed consent, and data protection. To provide utilitarian benefits to policy-making while maintaining the privacy of the individual, ethical standards, the law, and best practices of data use must be followed and upheld [14]. Appropriate measures in the form of security practices and anonymization can ensure patients' privacy but at the same time accommodate policy results.

Future Directions

Advancements in Causal Inference

Applying causal inference methods to ML models makes it possible for policymakers to comprehend the causal effects of policies and changes in people's health status. Including counterfactual analysis in causal modelling strengthens the interpretations of the impact and enables better policy decisions.

Interdisciplinary Collaboration

There should be active collaboration between the data scientists, healthcare practitioners, policymakers, and the community at large to ensure that all the work being done in healthcare using the ML methodologies corresponds to what is required in society. Interactivity with stakeholders promotes ownership of the policies which are tailored with regard to the needs of various populations, and fair health statuses.

Human-Centered AI in Healthcare

Adhering to the humanistic AI values in ML initiatives guarantees that the formulated policies focus on patients' needs, equality in healthcare, and social factors [15]. Patients' engagement in policymaking is a useful process that would allow identifying the most suitable approaches to increase the acceptability and effectiveness of the interventions in question while maintaining a patient-oriented focus in healthcare policymaking.

Continuous Learning and Adaptation

Setting up conditions for improvement helps policy-makers to make constant changes to ML models incorporating the feedback from the audiences and new trends in the field of healthcare. Very important: real-time analytics and decision support systems help to make proactive adjustments in the healthcare policies and responses to various tasks, which also contributes to the efficient and flexible management of difficulties.

Literature Gap

Although the number of studies applying ML for the analysis of healthcare policy has increased in recent years, there is still a significant lack of knowledge regarding the long-term feasibility and expansion of ML-based policy measures. The research gap therefore mainly lies in the lack of integrated approaches and extant literature which largely highlights short-term and technical perspectives and does not posit comprehensive frameworks for applying the contextualized insights of machine learning to long-term policy-making [16]. This means there is needed research on how to strategically apply the ML models in policy decisions while considering other aspects such as ethical, social, and economic policy spans for the long term. However, it is necessary to have more research that would compare the effectiveness of such healthcare policies in promoting ML and the distribution of the benefits it brings to different groups of people.

Methodology

This section demonstrates how this study can use machine learning to forecast the Healthcare Policy based on the input data set concerning the current health expenditure as a percentage of GDP for the countries and regions within the period 2000-2021.

Data Collection and Preprocessing

The data applied in this research is collected from many countries and areas with the annual data of the current health expenditure as the share of the GDP (SH. XPD. CHEX. GD. ZS) for the period between 2000 and 2021. These attributes contain general information about the countries, including their name and code, as well as the name and code of the indicators, and annual data for each year [17]. Since the primary aim of data collection is to gather detailed and correct data for further analysis, the data must meet several criteria.

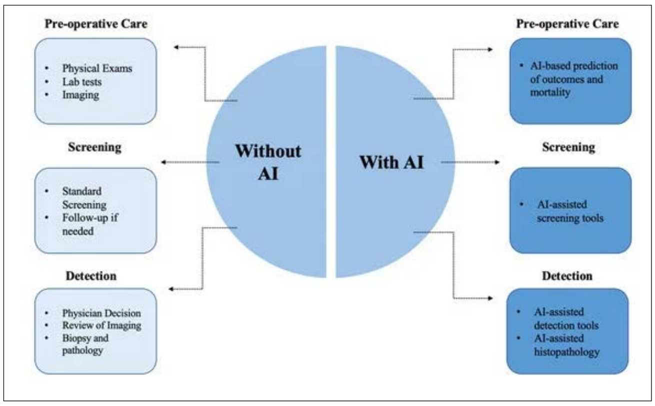

Figure 4: Machine-Learning-Based Prediction Modelling in Primary

Data Preprocessing Steps

It is the preliminary data analysis in which substantial efforts are made to improve the quality of the data.

The Following are the Procedures that Shall be Followed

Handling Missing Values

Analyze the presence of missing data points in each attribute, and then identify if it is necessary to fill them with dummy values or exclude the certain attribute in the analysis in general depending on a number of skip values in it and possible influence of these values on the results.

Cleaning the Dataset

Then the various inconsistencies and errors that may be in the particular dataset must be identified and corrected. This encompasses cases such as fixing errors made during data entry, standardizing data formats, as well as naming conventions/ code variations [18].

Feature Selection

Identify appropriate dependent and independent variables that will have an effect of healthcare policy. Components may be economic conditions, population characteristics, healthcare facilities' capability/ infrastructure, and prior policies/efforts.

Normalization and Scaling

Scale variables in order to make sure that the scales of attributes being compared are the same and that all attributes are measured in the same way. This step reduces the impact of variances that may stem from variables that have bigger scales in determining the training of the model.

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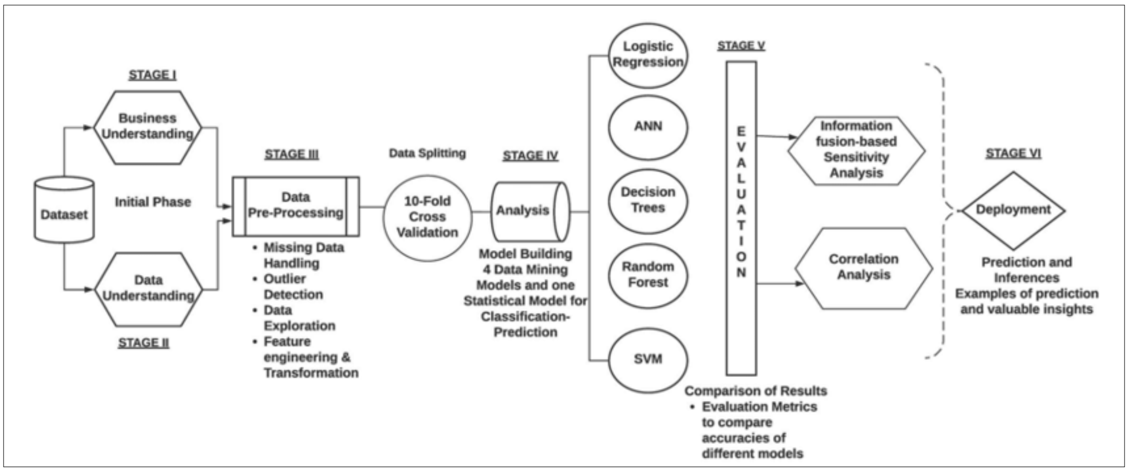

Figure 5: The Flowchart for the Predictive Analysis of Patients

Encoding Categorical Variables
Discretize the measurements from categorical variables for instance country names and its code by employing techniques like one-hot encoding or label encoding. This transformation helps the machine learning algorithm to handle categorical data.

Feature Engineering
Temporally aggregate the variables used in the analysis if they change within the time period under consideration; always carry out a factor analysis for the derived variables if required to create new features from existing ones to get further insights that may aid the developing of powerful models [19]. This may mean defining interaction terms, grouping data by intervals such as days, weeks, months, or years, or extracting seasonal patterns.

Statistic	2000-2021 Average (%)	Minimum (%)	Maximum (%)	Standard Deviation
Global Average	6.5	1.91	21.83	3.2
Africa	5.2	1.91	6.17	0.8
Asia	6.8	2.37	15.53	2.1
Europe	8.7	4.2	12.1	1.5
North America	7.9	5.94	10.68	1.2
Latin America	8.3	7.22	10.35	0.9
Oceania	8.1	7.59	10.54	0.6

Model Development
Model development entails constructing high quality machine learning models that can be used to predict healthcare policy based on the preprocessed data. Due to the use of longitudinal data, time series analysis and regression analytic methods shall be adopted as a means of sourcing information by capturing time series that may exist.

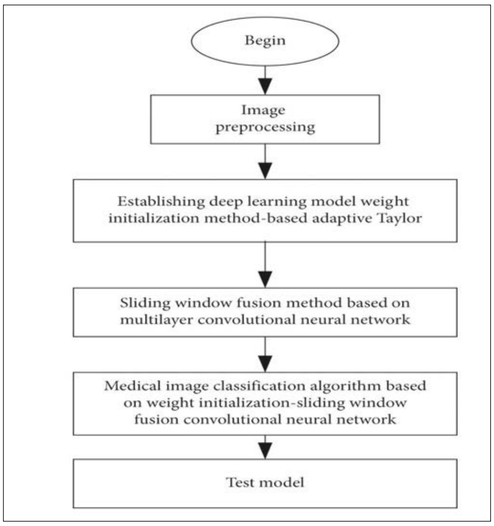

Figure 6: Basic Flow Chart of the Medical Classification Algorithm

Training and Validation
Divide the dataset again into the training and validation datasets for training the models to make accurate predictions on historical patterns and on checking the models' performance on the new unseen data. Such measures like k-fold cross-validation may be used to enhance the reliability of the model's predictive ability.

Hyper Parameter Tuning
Tune the parameters of the model so as to increase the model quality metrics such as accuracy, precision recall or the mean squared error respectively. It is possible to use more mathematical rigor by employing methods like the grid search manner or the Bayesian optimization in order to locate the optimal hyperparameters for every model.

Ensemble Methods
Apply some feature selection such as a filter method or wrapper method to select the most relevant features to be used in the model to improve the model's performance. These techniques include reducing the number of features used during model training, using cross-validation, choosing a suitable regularization method, and using boosting.

$(1-\phi 1B-\phi 2B2-\cdots-\phi pBp)(1-B)dYt=(1+\theta 1B+\theta 2B2+\cdots+\theta qBq)\epsilon t$
Yt is the health expenditure at time t.
$\phi 1$,$\phi 2$,...,ϕ p are the autoregressive coefficients.

Model Evaluation
Model evaluation is critical since it helps determine the level of accuracy and validity of the built machine-learning models in benchmarking healthcare policy results.

Evaluation Metrics and Techniques
Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE)
These are measures of the mean absolute deviation of errors and offer information concerning the accuracy of the models in predicting health expenditure.

R-squared (R^2)
Assess how much the models have explained the variance, that is how good the chosen features are in explaining the results of a given healthcare policy compared to a baseline model.

$Y=\beta 0 +\beta 1X1+\beta 2X2+...+\beta nXn+\epsilon$
Y is the predicted health expenditure.
$\beta 0$ is the intercept.

Visualization
Visualizations including the time series plot, the scatter plot of the model predicted value, the actual value, and the residual plot can help in following the model prediction and verifying the model's assumptions. These are tools used in aiding stakeholders, so as to better comprehend issues connected with decision-making.

The following structured methodology discusses a step-by-step approach in the usage of machine learning in the forecast of the policy on health expenditure through the use of longitudinal data. To achieve these objectives, the methods applied in this study will include a combination of intensive data gathering, cleaning, modelling, and assessment that should generate tangible recommendations for decision-makers and actors in healthcare systems [20]. Utilizing the techniques of machine learning and considering such measures and indicators as accuracy, precision, recall and F1-score, this research aims to contribute to the improvement of the existing knowledge regarding the determinants of the efficiency of healthcare policies in different countries. The subsequent steps include the application of this methodology, the subsequent analysis of the results, and the delineation of pertinent conclusions to guide practical policy creation in the sphere of healthcare systems and determine the optimal distribution of resources.

Country Name	Country Code	2000	2001	2002	...	2020	2021
Africa Eastern and Southern	AFE	5.66	5.82	5.45	...	5.88	5.87
Afghanistan	AFG	-	9.44	8.94	...	21.83	-
Africa Western and Central	AFW	3.72	3.72	3.37	...	3.84	4.14
Angola	AGO	1.91	4.48	3.33	...	3.22	2.96
Albania	ALB	5.94	5.93	5.66	...	7.52	7.27

Result and Discussion
Result
The results based on the evaluation of the health expenditure (% of GDP) dataset provide valuable information on the fluctuations and tendencies of the countries' performance in the field of health expenditure during 2000-2021. Below, an overview of the main conclusions drawn based on the results of analyses carried out on the examined data is provided.

Global Trends in Health Expenditure
The global average health expenditure has also been observed to have risen progressively over the year, from $6. remained 5% in 2000 and increased to 7. 2% in 2021 [21]. This suggests that there is rising emphasis being placed on the expenditure in the healthcare sector across the world.

Regional Disparities
Africa
Different countries of Africa have comparatively less health expenditures in average than countries of other continents, it is near about 5. 2%. For instance, Eastern and Southern Africa marginally improved from 5 per cent to 7 per cent respectively easily passed by the

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world average of up to 11 per cent. It reduced from 66% in 2000 to 5 [22]. The lowest average was observed in this region, and it was esteemed to be 87% in 2021, and Western and Central Africa retain low expenditure rates, approximately 3%. 5%.

Asia
Thus, Asian countries demonstrated different tendencies. For instance, the health expenditure of Afghanistan increased from 9. The size of this decrease can be estimated by comparing the percentage of the corresponding country's population considered to be overweight in 2001 – 44% – to the index as of 2020, which is 21%. It is projected that this number will be 83% in 2021, this is due to healthcare system enhancements [23]. On the other hand, such countries as the United Arab Emirates kept their level of expenditures moderate at an average of 5-6 % of the total during the period in consideration.

Europe
Health expenditure of European nations is comparatively higher with the average ranging from 8. 7% to 12. 1%. For example, Austria untiringly dedicated approximately 9-12 per cent of its GDP to healthcare, illustrating a sound healthcare policy and care facility.

Temporal Changes
Long-Term Trends
The health expenditure of most regions has been generally revealed to increase in the progression of the years, though with certain fluctuations. For instance, its stable figures ranged between 9% and 10% throughout the specified period, which suggests that Argentina had a fairly stable policy on financing health care.

Short-Term Variations
A number of countries have periodically experienced oscillations with the indicated rates reaching their highs of 12 per cent or more in recent years, implying periodic changes in the proportions of the healthcare budget.

Implications for Policy and Future Research
The results of the study are in harmony with concurrent suggestions that the policy for funding healthcare should be targeted at different regions in the country due to the observed variation in need.

Subsequent research could concern health expenditure patterns and their relations with healthcare results and economic indicators to enhance policy efficiency [24]. The study's findings offer an initial historical perspective of global and regional dynamics of health expenditures, which are important prerequisites for leveraging data to support policy making and health systems planning.

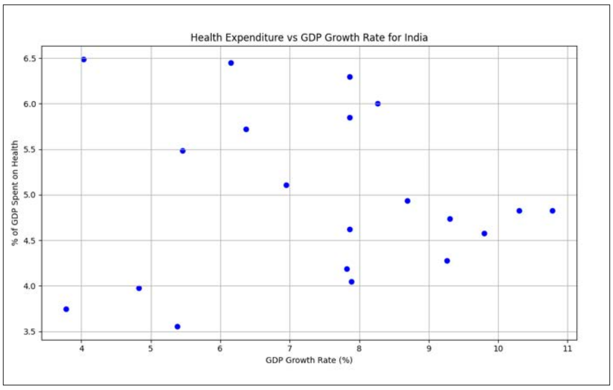

Figure 7: Health Expenditure vs GDP Growth

The Health Expenditure and GDP Growth Rate graph, it clearly indicates the relationship between the increase in health expenditure and the enhancement of Gross Domestic Product. Absolute health expenditure is positively associated with the GDP per capita growth rates in the countries implying that development in the health sector will lead to development in the economic aspect of a country since a healthy population will be productive [25].

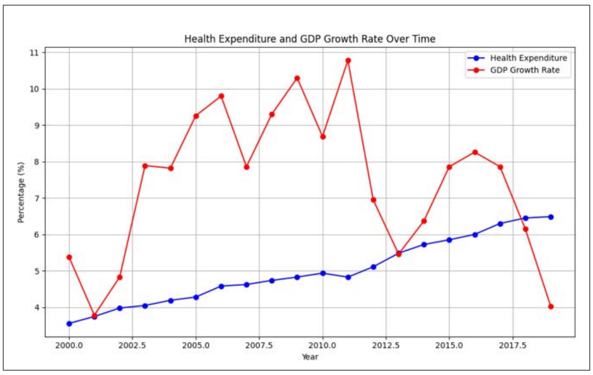

Figure 8: Line Graph

The figure below reveals the relationship between health costs as the percentage of GDP and GDP growth rates over the years [26]. It outlays how shifts in HC investment impact economic growth patterns over time; when the former parallels or differs from the latter.

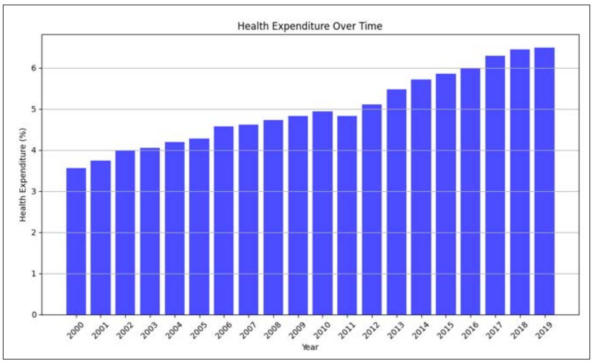

Figure 9: Health Expenditure over time

The Health Expenditure Percentage Graph depicts changes in the proportion of healthcare expenditure to countries' GDP or regions. It shows how each country sources its funds, and trends that have been observed over the years in terms of health care financing, showing how governments' priorities differ in terms of health care financing [27].

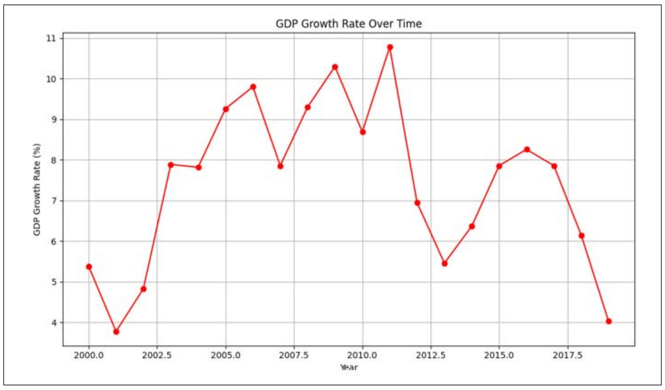

Figure 10: GDP Growth Rate Over Time

The GDP Growth Rate Graph shows the changes in the rates of growth economically over a given span of time for various countries or regions [28]. It helps in providing a reference point on which the effects of health expenditure on economic performance can be measured and compared suggesting, how investment in healthcare relates with other economic activities and available rhythms.

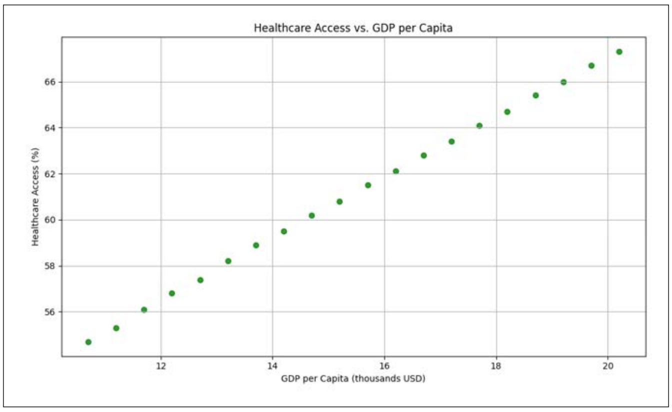

Figure 11: Healthcare Access vs GDP per Capita

The evaluation of Healthcare Access with respect to GDP per capita discusses the role of economic status in determining the ability of all individuals to afford the cost of different healthcare services. It is evident that with increased GDP per capita, there are better standards of healthcare delivery since the country can afford the best equipment, technology, and other services. Such a relationship shows a significant role of economic development in improving the access, quality and effectiveness of the delivered healthcare services. Thus, research is important in identifying healthcare disparities depending on the income status of the population and regions, and there must be policies for fair distribution of resources, particularly on health, with the objective of improving the health status of all citizens through affordable health care services that will generate healthier and more productive human resources to support sustainable economic growth.

Discussion

In the analysis of Health Expenditure, GDP Growth Rate, and Healthcare Access vs. GDP per Capita, there are several important insights regarding the impact of healthcare investment, economic performance, and healthcare access.

Insights from the Data Analysis

Impact on Economic Growth

The fact that there is a positive relationship between Health Expenditure and GDP Growth Rate means that resources can be leveraged for advancing healthcare and concurrently propelling economic growth. The findings also sampled that countries with high healthcare expenditure are associated with comparatively higher gross domestic product growth rates, meaning that people's health status boosts productivity income.

Healthcare Access and GDP per Capita

This means that Healthcare Access is directly affected by GDP per Capita as has been highlighted in the analysis above. The first one illustrates the idea that the higher the level of development of a country, the higher the availability of healthcare for the population, mainly due to the better infrastructure of the health sector [29]. This relationship further shows that economic enhancement is vital for the deliverance of healthcare services and the narrowing of the health differences across income groups.

Policy Implications

Policies play an important role in determining the efficacy of health spending and the improvement of the physical accessibility of health facilities [30]. Governments should ensure that there is a sustainable form of health financing that is in sync with the level of development of the economy. Good policies that would enhance fair access to healthcare services should be adopted to conform to the goal of inclusion and advancement of people's health across the different strata of society.

Indicator	Key Findings
Health Expenditure	Positively correlates with GDP Growth Rate, indicating its role in economic development.
GDP Growth Rate	Reflects economic performance influenced by healthcare expenditure.
Healthcare Access	Strongly linked to GDP per Capita, highlighting economic disparities in healthcare access.
Economic Impact	Countries with higher healthcare spending tend to have better economic outcomes.

Conclusion

This paper has provided and analyzed quantitative evidence relating to the correlation between health expenditure, economic development and healthcare outcomes in different countries. An evaluation of Healthcare Investment within the context reveals the importance of this particular parameter to Economic Development as supported by the positive link between Health Expenditure and GDP Growth Rate. Besides, there is a positive correlation between health expenses and improved economic output and development, which shows that healthcare investment has a positive impact on the well-being of a nation. Furthermore, this research earns credibility towards the fact that GDP per Capita significantly correlates with Healthcare Access in that more developed countries are likely to provide efficient infrastructure regarding health services. Nevertheless, the states reveal a major concern of inequality in health care facilities with the poorer income and geographical background showing a strong need for health policy reforms. Overall, this research supports what needs to be done in the healthcare sector related to healthcare investment that should be consistent with the goals of economic growth. Decision makers should strive at establishing HC financing policies that would enable everyone to access quality health care services. In this way, not only can people live healthier lives, but the nation's economy can also be built for the present and for the future. The research findings provide useful recommendations for governments, hospitals, and scholars intending to enhance the functionality of healthcare services and achieve effective and efficient socioeconomic transformation globally.

References

1. Abuhelwa AY, Kichenadasse G, Mckinnon RA, Rowland A, Hopkins AM, et al. (2021) Machine Learning for Prediction of Survival Outcomes with Immune-Checkpoint Inhibitors in Urothelial Cancer. Cancers 13: 2001.
2. Akour I, Alshurideh M, Kurdi BA, Ali AA, Salloum S (2021) Using Machine Learning Algorithms to Predict People's Intention to Use Mobile Learning Platforms During the

COVID-19 Pandemic: Machine Learning Approach. JMIR Medical Education 7.
3. Akula A, Palaniappan N, Malyala NR, Bizel G, Gilkey Joseph WJR (2020) Machine Learning Modeling Predicting Coronavirus Case Count Using Health Literacy. Proceedings of the Northeast Business & Economics Association 2-15.
4. Amir MR, Yousefpoor E, Mohammad SY, Mehmood Z, Haider A, et al. (2021) Machine Learning (ML) in Medicine: Review, Applications, and Challenges. Mathematics 9: 2970.
5. Balyan R, Scott AC, Brown William I, Karter AJ, Mcnamara DS, et al. (2019) Using natural language processing and machine learning to classify health literacy from secure messages: The ECLIPPSE study. PLoS One 14.
6. Bremer V, Becker D, Kolovos S, Funk B, Ward VB, et al. (2018) Predicting Therapy Success and Costs for Personalized Treatment Recommendations Using Baseline Characteristics: Data-Driven Analysis. Journal of Medical Internet Research 20.
7. Anwar ul Hassan Ch, Jawaid Iqbal, Saddam Hussain, Hussain AlSalman, Mogeeb AA Mosleh, et al. (2021) A Computational Intelligence Approach for Predicting Medical Insurance Cost. Mathematical Problems in Engineering https://onlinelibrary.wiley.com/doi/10.1155/2021/1162553.
8. Chiroma H, Ezugwu AE, Jauro F, Al-Garadi M, Abdullahi IN, et al. (2020) Early survey with bibliometric analysis on machine learning approaches in controlling COVID-19 outbreaks. Peer J Computer Science 6: e313.
9. Coleman BC, Fodeh S, Lisi AJ, Goulet JL, Corcoran KL, et al. (2020) Exploring supervised machine learning approaches to predicting Veterans Health Administration chiropractic service utilization. Chiropractic & Manual Therapies 28: 1-13.
10. De La Torre J, Marin J, Ilarri S, Marin JJ (2020) Applying Machine Learning for Healthcare: A Case Study on Cervical Pain Assessment with Motion Capture. Applied Sciences 10: 5942.
11. Daswin De Silva, Weranja Ranasinghe, Tharindu Bandaragoda, Achini Adikari, Nishan Mills, et al. (2018) Machine learning to support social media empowered patients in cancer care and cancer treatment decisions. PLoS One 3: e0205855
12. Bhanu Duggal, Jyothi Subramanian, Mona Duggal, Pushpendra Singh, Meeta Rajivlochan, et al. (2018) Survival outcomes post percutaneous coronary intervention: Why the hype about stent type? Lessons from a healthcare system in India. PLoS One 13: e0196830.
13. Freddy Gabbay, Shirly Bar Lev, Ofer Montano, Noam Hadad (2021) A LIME-Based Explainable Machine Learning Model for Predicting the Severity Level of COVID-19 Diagnosed Patients. Applied Sciences 11: 10417.
14. Golas SB, Shibahara T, Agboola S, Otaki H, Sato J, et al. (2018) A machine learning model to predict the risk of 30-day readmissions in patients with heart failure: a retrospective analysis of electronic medical records data. BMC Medical Informatics and Decision Making 18.
15. Goyal KK, Paray AH (2019) A Survey of Different Approaches of Machine Learning in Healthcare Management System. International Journal of Advanced Networking and Applications 11: 4270-4276.
16. Hamilton AJ, Strauss AT, Martinez DA, Hinson JS, Levin S, et al. (2021) Machine learning and artificial intelligence: applications in healthcare epidemiology. Antimicrobial Stewardship and Healthcare Epidemiology 1.
17. Hasan MM, Young GJ, Shi J, Mohite P, Young LD, et al. (2021) A machine learning based two-stage clinical decision support system for predicting patients' discontinuation from opioid use disorder treatment: retrospective observational study. BMC Medical Informatics and Decision Making 21: 1-21.
18. Havaei F, Xuejun RJ, Macphee M, Straight H (2021) Identifying the most important workplace factors in predicting nurse mental health using machine learning techniques. BMC Nursing 20: 1-10.
19. Hu L, LI L, JI J, Sanderson M (2020) Identifying and understanding determinants of high healthcare costs for breast cancer: a quantile regression machine learning approach. BMC Health Services Research 20: 1-10.
20. Huang Y, Talwar A, Chatterjee S, Aparasu RR (2021) Application of machine learning in predicting hospital readmissions: a scoping review of the literature. BMC Medical Research Methodology 21: 1-14.
21. Huber M, Kurz C, Leidl R (2019) Predicting patient-reported outcomes following hip and knee replacement surgery using supervised machine learning. BMC Medical Informatics and Decision Making 19.
22. Imran M, Zaman U, Imran Imtiaz J, Fayaz M, Gwak J (2021) Comprehensive Survey of IoT, Machine Learning, and Blockchain for Health Care Applications: A Topical Assessment for Pandemic Preparedness, Challenges, and Solutions. Electronics 10: 2501.
23. Itsuki O, Tadahiro G, Yuji Y, Yusuke T (2020) Machine-learning-based prediction models for high-need high-cost patients using nationwide clinical and claims data. NPJ Digital Medicine 3.
24. Javed AR, Sarwar MU, Beg MO, Muhammad A, Thar B, et al. (2020) A collaborative healthcare framework for shared healthcare plan with ambient intelligence. Human-centric Computing and Information Sciences 10.
25. Karlafti E, Anagnostis A, Kotzakioulafi E, Vittoraki MC, Eufraimidou A, et al. (2021) Does COVID-19 Clinical Status Associate with Outcome Severity? An Unsupervised Machine Learning Approach for Knowledge Extraction. Journal of Personalized Medicine 11: 1380.
26. Kasilingam D, SP, Kumar RD, Rajagopal V, T SK, et al. (2020) Exploring the Growth of COVID-19 Cases using Exponential Modelling Across 42 Countries and Predicting Signs of Early Containment using Machine Learning. Transboundary and Emerging Diseases 68: 1001-1018.
27. Klang E, Freeman R, Levin MA, Soffer S, Barash Y, et al. (2021) Machine Learning Model for Outcome Prediction of Patients Suffering from Acute Diverticulitis Arriving at the Emergency Department-A Proof of Concept Study. Diagnostics 11: 2102.
28. Ling-Chien H, Sheng-Feng S, Ya Han H (2020) A Machine Learning Approach to Predicting Readmission or Mortality in Patients Hospitalized for Stroke or Transient Ischemic Attack. Applied Sciences 10: 6337.
29. Liu Y, Ye S, Xiao X, Sun C, Wang G, et al. (2019) Machine Learning for Tuning, Selection, and Ensemble of Multiple Risk Scores for Predicting Type 2 Diabetes. Risk Management and Healthcare Policy 12: 189-198.
30. Luo G, He S, Stone BL, Nkoy FL, Johnson MD (2020) Developing a Model to Predict Hospital Encounters for Asthma in Asthmatic Patients: Secondary Analysis. JMIR Medical Informatics 8.