Evaluating the Impact of Universal Health Coverage Policies on Population Health Outcomes Using Big Data Analytics for Comprehensive Policy Assessment

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KEYWORDS

Universal, Health, Coverage, Policies, Population, Health, Outcomes, Big Data, Comprehensive, Policy, Assessment, Fragmented Systems

ABSTRACT

Universal Health Coverage (UHC) aims to eliminate financial barriers to care which is important for everyone's affordability. Thus, it is helpful to study how UHC affects population health outcomes and where it may be headed in the future. Big Data Analytics provides good tools for scrutinizing those principles and their results on a huge scale. Communities differ in terms of their health outcomes; and health systems are complex. This paper tries to address these among other issues by integrating big data sets that are diverse and analysing them together. As an innovative way of examining universal health coverage initiatives' impact on populations, researchers propose the Comprehensive Analysis of Fragmented Health Systems (CA-FHS). CA-FHS uses Big Data Analytics to compile and analyse information from many different sources thereby giving an exhaustive breakdown of health outcomes by demography as well as geographic area. This would allow trends or patterns not seen using conventional evaluation tools to be discovered. It encompasses public health, policy-making, as well as healthcare management concerns. In this way, the method may bring out the strengths and weaknesses inherent in the healthcare system such that policies are recommended for change while resource allocation is done for bettering UHC-related consequences internationally. It will enable the evaluation of long-term effects resulting from these projects so that they can meet their goals eventually. The process will involve creating hypothetical policy scenarios and then assessing how these would affect population's historical health outcomes through use of historical data simulation techniques; thus providing input into potential policy choices at federal level concerning evidence-based recommendations towards achieving improvement in health status.

1. Introduction

The goal of health systems should be UHC, which means that everyone who needs healthcare (prevention, treatment, rehabilitation, and palliative care included) should be able to get it without going into serious debate [1]. Human capital and economic progress cannot exist without good health. Because of this, people can work, and children are able to go to school [2]. Healthcare spending, therefore, is an investment in people rather than a cost [3]. Because health is both a result of and a necessity for sustainable development, as well as an indication of success in all three aspects of sustainability, UHC is crucial to attaining the CA-FHS [16]. Assuring the provision of healthcare services when required promotes social cohesion, protects people from diseases, promotes economic development, combats poverty, and offers universal access to high-quality health systems [5]. It may be difficult to evaluate health status improvement properly in most datasets, even though this is the ultimate purpose of healthcare services [6]. Consequently, research has shifted its attention to intermediate outcomes, such as the frequency of surgical operations, the number of prenatal visits, the number of doses of vaccines administered to children, and similar indicators [21]. Even when comparing health systems with comparable income levels, educational attainment, and healthcare spending, performance varies[4]. Their capacity to accomplish vital health goals is impacted by this performance gap [10] [8]. WHO reports that health systems around the globe waste between twenty percent and forty percent of their budgets due to several types of inefficiencies [22]. The results of CA-FHS have the ability to make it easier to monitor trends in health system efficiency, improvements over time, and nations' advancements towards universal health coverage [19][11]. The main contribution of this paper is as follows: By combining CA-FHS, the health outcomes in their whole across all demographics and regions, which may shed light on issues that were previously difficult to assess. When it comes to public health and policy decisions, a thorough evaluation is essential, and CA-FHS can provide just that by using Big Data Analytics to spot patterns and trends that show where health systems excel and where they fall short[7]. By contributing to the ongoing improvement of UHC projects, it helps to improve the general efficiency and dependability of the system, as well as the allocation of resources. The remaining of this paper is structured as follows: In section 2, the related work is given. In section 3, the proposed methodology is explained and in section 4, the result and discussion are covered and finally, in section 5 the paper is concluded.

2. Literature Review

Utilizing a set of tracer indicators, it can quantify the extent to which universal health care provides certain services. Using publicly accessible national data, our universal health care service coverage index can be quickly and easily calculated by data mining if new indicators become available via SDG monitoring, they may be added to the index[14]. It may use these tracer indicators to see how far down the road to universal health care, but they don't tell what service coverage by Hogan, D. R. et al., [18]. Improving healthcare service delivery is the goal of this research project, which aims to use eHealth and offer a conceptual cloud computing architecture. The study's overarching goal is to spark fresh forms of cooperation in the development of a healthcare system based on evidence and value. The results show that dealing with the delicate nature of medical records is still difficult by Mgozi, T. et al., [12]. A more flexible and principled approach to exploring treatment-effect heterogeneity is offered by causal machine learning methods, in contrast to standard subgroup analyses that are limited to considering a restricted number of pre-defined subgroups is proposed by Kreif, N. et al.,[13]. The artificial intelligence found extensive microdata on health-related employment in 1404 country-years of labour force survey data and 69 country-years of census data via the International Labor Organization and Global Health Data Exchange databases. Using the World Health Organization's National Health Workforce Accounts, The International Standard Classification of Occupations was used to create a map of all occupational coding systems by Haakenstad, A. et al., [20]. The deep learning model surpassed all other methods in the preliminary comparison testing[17]. This methodology's efficacy and appropriateness were shown when the suggested model considerably improved the classifier's performance when compared to several other state-of-the-art approaches in the biomedical area by Tariq, M. U. et al., [15].

3. Methodology

There is a wide range in performance across health systems, even when controlling for factors like income, education, and healthcare spending. Critical health goals are hindered by this performance gap. To assess development, compare nations, and direct policy choices along both dimensions, the UHC index assesses and captures both aspects of the UHC concept.

Universal Health Coverage Policies on Population Health Outcomes

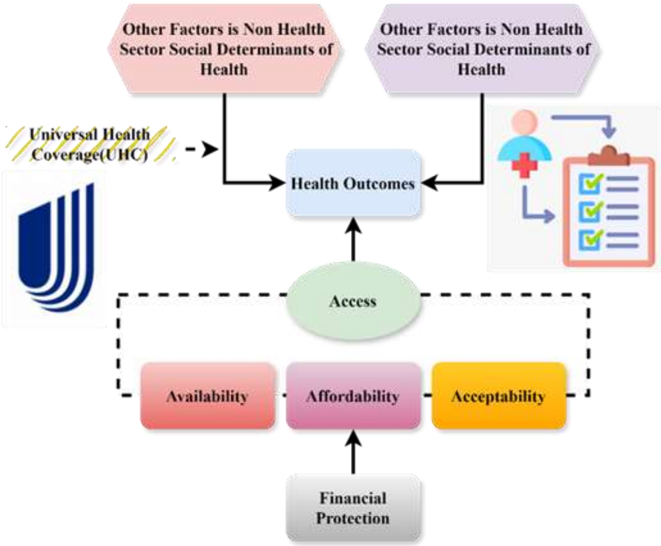

Figure 1. Diagram of Universal Health Coverage Policies on Population Health Outcomes

Figure 1 shows the aspects of healthcare access impact health outcomes. "Access," the central notion in the graphic, is affected by three important factors: cost, availability, and acceptability. The degree to which people can get essential healthcare services is determined by these components. Emphasizing its function in reducing financial obstacles to healthcare access, financial protection is shown as a core factor. Encircling the main points are the "Other Factors in Non-Health Sector Social Determinants of Health," which indicate that health outcomes are likewise considerably impacted by more extensive social, economic, and environmental variables that do not pertain to the healthcare industry specifically. The need for all-encompassing approaches to better health outcomes is highlighted by this holistic perspective, which highlights the complex character of health factors.

Comprehensive Analysis of Fragmented Health Systems

All these systems affect the healthcare budget and the broader economic climate that health policies are a part of. The middle segment emphasizes societal value by balancing rewards and costs. When evaluating the success of health policy in raising the standard of living for the public, it considers measures like happiness and utility.

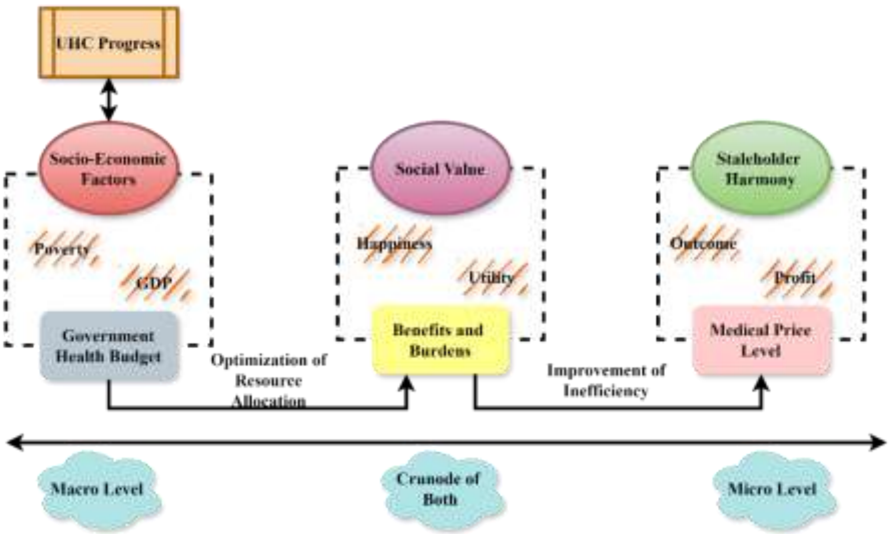

Figure 2. Architecture of Comprehensive Analysis of Fragmented Health Systems Levels

Figure 2 shows a model for assessing UHC development from several angles, including socioeconomic status, social value, and stakeholder harmony. These three (3) macroeconomic variables; poverty, gross domestic product, and government health budget; are significant in the achievement of universal health coverage.

Healthcare pricing is responsible for the outputs of patient care as well as profitability, and it is at this level that the last part focuses on how politicians, doctors, and patients combine their efforts and objectives to ensure they achieve better health outcomes. In summary, these components provide an extensive perspective on UHC encompassing macroeconomics and micro stakeholders' dynamics towards sustainable equitable healthcare.

Big Data Analytics for Comprehensive Policy Assessment

A detailed procedure for assessing the results of UHC (Universal Health Coverage) initiatives with the use of Big Data Analytics. The process starts with gathering data from a variety of sources, such as health records, policy data, and geography data. Hypothetical policy scenarios are generated by integrating these varied sources

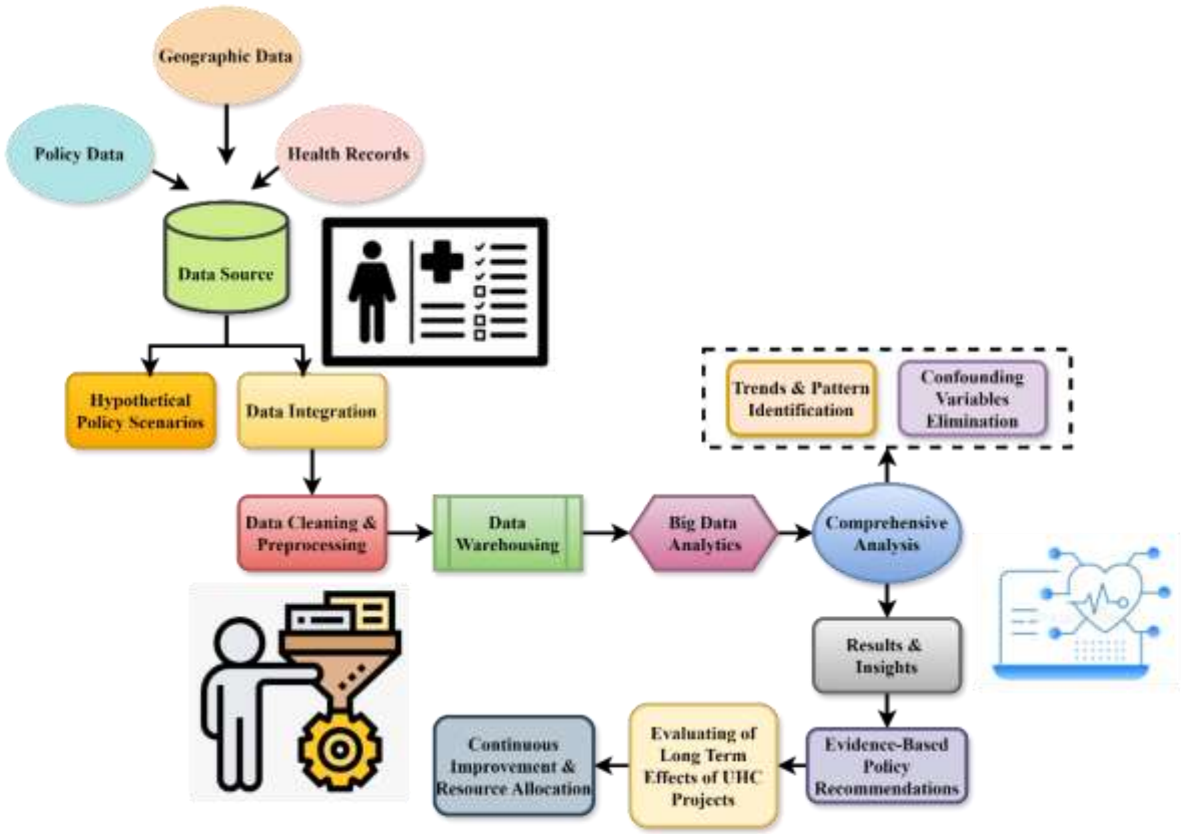

Figure 3. Flow Diagram of Big Data Analytics for Comprehensive Policy Assessment

Important first stages in ensuring data quality include cleaning and preprocessing, and then data warehousing is used to store and manage the cleansed data. The next step is to use Big Data Analytics to spot patterns and trends while removing any factors that might affect the findings. At its heart is the complete analysis, which draws conclusions and insights from the data by synthesising it. With the goals of constant development and efficient use of resources, this study assesses the impact of UHC initiatives over the long run is shown in figure 3. In the end, it want to assist fulfill the goals of UHC programs and improve health outcomes by providing stakeholders and policymakers with evidence-based policy suggestions. Better health systems and healthier populations are the results of this process's emphasis on solid data analysis as a foundation for health policy.

Using a mathematical calculation to determine the feasibility of the proposed method

Mathematical computations are used in quantitative analysis to evaluate the practicability and possible effect of the suggested approach. This encompasses both simulations to predict outcomes under different situations and statistical modeling to evaluate the accuracy and robustness of data. The method's efficacy and practical applicability may be rigorously validated by these calculations.

$$t_{q+1} = Ge_{s-1} + R_{xzq} - \left(1 + \frac{[Z] + G_{q-1}}{\sqrt{h + qk}}\right) - \sum_{t=1}^{l}(r - q) \qquad (1)$$

Equation 1 may be linked to the Comprehensive Analysis of Fragmented Health Systems method. In this instance, the health outcome at the next time step will be indicated by t_{q+1}, demographic and geographic factors by Ge_{s-1} and G_{q-1}, policy influences by R_{xzq} and the overall impact of interventions over time by the total term $\sum_{t=1}^{l}(r-q)$ could be represented.

$$c^{g}(q-1) = d\sum_{i=1}^{g}\frac{R_{t+1}}{\partial^{2}} - \frac{(n-1) - R^{l-1}}{x+rq} - i_{kq}(r-1) \qquad (2)$$

The integration of different factors $c^{g}(q-1)$ affecting health outcomes is illustrated by equation 2 in the same way that CA-FHS integrates diverse datasets for a thorough evaluation. To improve policy analysis and decision-making R_{t+1}, this mathematical technique ∂^{2} helps $i_{kq}(r-1)$and patterns trends in health outcomes $\frac{(n-1)-R^{l-1}}{x+rq}$ across various populations and geographies.

$$d_{r}^{s-1} = \frac{F_{s}}{R_{q}-1} + (1-\propto x) - d_{x} + N - \frac{N}{mX}(q+1) \qquad (3)$$

Equation 3 is to see it as a model that incorporates many factors that impact health outcomes. In this case, d_{r}^{s-1} might stand for a health outcome in a particular state $s-1$, impacted by variables like F_{s} (perhaps representing a health service factor), $R_{q}-1$ (a resource metric), $(1-\propto x)$ (a demographic adjustment), d_{x} (an existing health metric), N (a population variable), and $\frac{N}{mX}(q+1)$ (a policy factor).

$$E_{r} = \frac{i}{m-q}(b-r) + d^{xs} - \frac{[1+q] - \left(z_{klq} - mo^{v}\right)}{q+n^{l}} \qquad (4)$$

A complicated model that could be used in the CA-FHS framework to examine health outcomes by taking into E_{r} consideration factors like distributing resources $\frac{i}{m-q}$, demographic variables $(b-r)$, and external influences $\left(z_{klq} - mo^{v}\right)$ is equation 4 multi-faceted $[1+q]$ components make it useful for simulating and predicting the impact of various UHC strategies on health results, $q+n^{l}$ which in turn helps researchers spot patterns and make informed policy choices.

$$N\left(\{R_{k}\},\{V_{l}\}\right) = \frac{1}{N_{class}}\sum_{k}^{l} N_{class}\left(\alpha_{l},\alpha_{l}^{*}\right) + g^{q} - \sum\nolimits_{l}^{q}\delta_{k}^{*} \qquad (5)$$

Equation 5 can be associated with the CA-FHS method. To make informed policy choices $N\left(\{R_{k}\},\{V_{l}\}\right)$, it is necessary to conduct sophisticated analyses N_{class} of health data using $\alpha_{l},\alpha_{l}^{*}$ Big Data Analytics. This calculation encapsulates g^{q} the intricacy of attributing results to UHC by taking into account $\sum_{l}^{q}\delta_{k}^{*}$ the effect of various groups and confounding factors.

$$\{(h1,r1)\},(h2,r2),\ldots,(hq,rs), g = \left(h1,\ldots,h_{q},h1,\ldots,h_{q}\right)^{F} \qquad (6)$$

The Equation 6 analysis is structured across different dimensions and pertains to health outcomes $h1$ and related resources $r1$. As it pertains to CA-FHS, this equation shows how various medical information $h1$ and resource indicators hq, rs are combined into a complete function g to find patterns and trends, that assist with evaluating UHC policies and how they affect health outcomes.

$$|(h1r2 - r1h2) + (h2r4 - r2h4) + \cdots + (h_{n}r1 - r_{n}h1)/2| \qquad (7)$$

Equation 7 may represent the combined effect of regional and demographic differences in the distribution of resources $h1r2$ and health determinants $r1h2$ within the framework of the Extensive $h2r4$, divided analysis of health outcomes $h_{n}r1$. Incorporating these computations allows $-r_{n}h1$ to find complex $2h4$ trends in health outcomes, which allows for a strong assessment of UHC programs.

$$\partial \complement\left(\text{Population}(y) \wedge \rho\tau\left(\text{Time}(a) \rightarrow \text{Health}(a,b)\right)\right) \qquad (8)$$

Equation 8 supports the $\text{Population}(y)$ approach as it shows how time, is an important factor in the multifactorial analysis. In a similar, $\rho\tau$ uses analysis of efficiency to analyze intricate health systems, taking into account a wide range $\partial \complement$ of factors to shed light on how $\text{Health}(a,b)$ policies affect the health of populations.

To assess UHC policies affecting populations' health outcomes, the suggested approach, CA-FHS, uses Big Data Analytics. Different communities and health systems have different levels of health outcomes which CA-FHS seeks to address through the compilation and analysis of large amounts of diverse data. This technique applies advanced analytic tools that help control or remove any intervening variables when assessing programs that cause UHC to make it more accurate. Health system advantages and drawbacks may be better understood, policy modifications can be informed, and resource allocation can be optimized with the help of this technique, all of which contribute to better health outcomes.

4. Results and discussion

In this section, the proposed method CA-FHS evaluates the health outcome and efficiency for the better outcome when compared to existing methods (ML,AI,CC,DM)

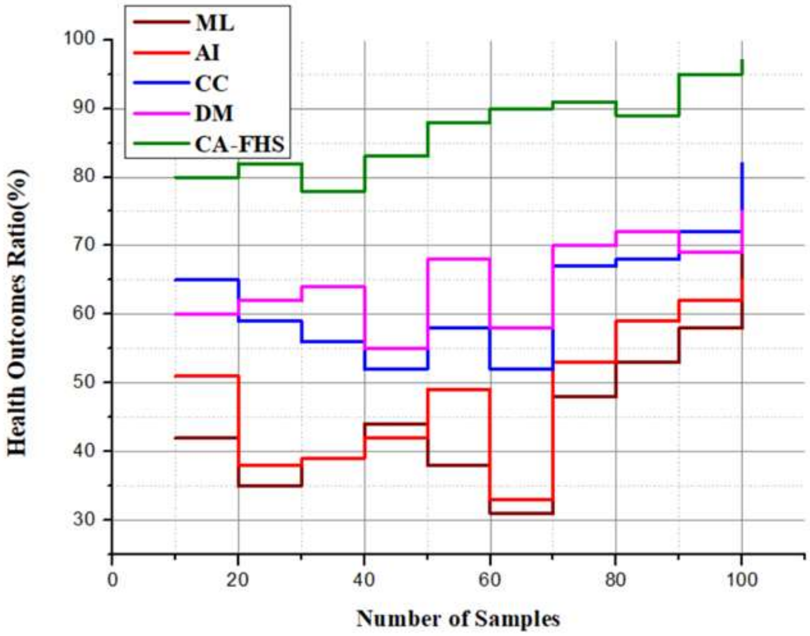

Figure 4. Analysis of Health Outcomes

Figure 4 shows the analysis of health outcomes focuses on measuring the effects of medical care on the welfare of patients, and it accomplishes that through gathering data from various sources including electronic medical records, surveys, and health insurance claims that quantify outcomes such as death rates, illness rates, or quality of life. Besides, machine learning and statistics can also be used to identify patterns, trends, and relations to predict fissures. Furthermore, if these researches are associated with geography/race groups then they will be in a better position to understand how healthcare systems function – thus addressing inequalities. Consequently, this leads to improved healthcare delivery; resource allocation; and finally evidenced-based policies within public Health.

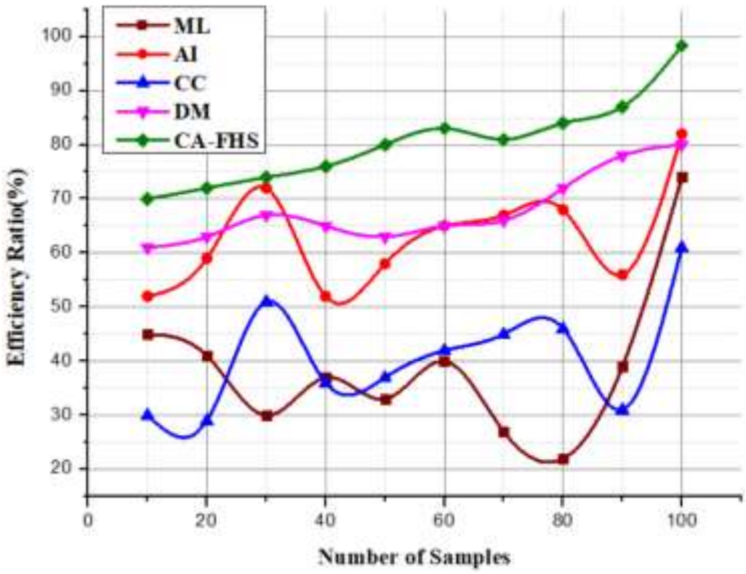

Figure 5. Analysis of Efficiency

Figure 5 shows the efficiency analysis' objective is to get a process or a system producing more output with less input effort. Indicators for measuring resource efficiency comprise time spent on different tasks, money used or resources consumed during this study process. Some methods which are used to capture inefficiencies as well as areas for improvement include: data envelopment analysis (DEA) and stochastic frontier analysis (SFA). For instance, taking healthcare as an example when we talk about wastage in health services provision involves finding out how hospitals use their resources efficiently when treating patients. Therefore efficiency analysis optimizes resource allocation by identifying best practices which enhance system performance leading to minimal waste generation coupled with increased overall output. The main objective is seeking higher outputs with lesser inputs of the resources into one system so that its performance may improve Efficiency Analysis and Health Outcomes. By using methods like data envelopment analysis (DEA) and stochastic frontier analysis (SFA), inefficiencies can be pointed out alongside areas that can be made better by looking at time money resource consumption among other factors which determine resource efficiency in some processes.

5. Conclusion and future scope

To achieve UHC, healthcare system must make better use of big data to revolutionize healthcare delivery, boost patient outcomes, and increase healthcare efficiency and cost-effectiveness. To reap the advantages of big data without infringing on people's privacy or rights, it is critical to resolve ethical and privacy problems. To achieve UHC, it is crucial to implement larger social and economic policies that tackle the root causes of healthcare inequalities and injustices. There are still significant differences across nations and economic brackets, and the worldwide UHC score is still far from ideal. Most health systems, according to our research, are inefficient, and this is true across all income brackets and World Health Organization regions. Even more crucially, the research shows that health systems are far more efficient in their pursuit of UHC when they invest in PHC. Health systems may be more efficient in their pursuit of UHC if there is coordinated legislation to that end and strong leadership at the regional, national, and international levels.

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