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THE USE OF DIGITAL HEALTHCARE SYSTEMS TO PREDICT DISEASES

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ABSTRACT

Smart health care depends heavily on a resilient and strong digital infrastructure. Telemedicine, Electronic Health Records (EHR), Fitness Trackers, Wearable Devices that monitor heart rate, steps, sleep cycles and many other digital health-related measures are already used as indicators of what a future system of health technology will look like. The purpose of this paper is to examine the existing research studies to determine if it is possible to forecast health based on the data available from such devices. Further, in the Indian context, where Unique Health ID (UHID) is already being implemented, this paper aims to extend the functionality of the UHID and analyze the viability of integrating the UHID with data sources for predicting health. Predicting and forecasting health will benefit all stakeholders in the healthcare ecosystem. Accurate disease forecasting models would be extremely helpful for epidemic and pandemic prevention and control. This research examines the potential for health forecasting and the challenges associated with its development.

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KEYWORDS

health forecasting, predictive health analytics, UHID

INTRODUCTION

The backbone of today's health care system is a strong and resilient digital infrastructure. As electronic medical records become more prevalent, innovators will gain new insights into human health. As a result of big data, Machine Learning, Artificial Intelligence, and IoT software applications, predictive health analysis is now possible. We already see the beginnings of a future health technology system through telemedicine, electronic medical records, teleradiology, and fitness trackers monitoring heart rate, steps, sleep cycle, and many other digital health-related metrics.

A healthy life is what customers want, but the focus of healthcare is to treat illnesses rather than prevent them. [1] However, it is becoming increasingly common to see the industry shift away from the reactionary approach to treating illnesses towards a more proactive, preventative, and human-centered approach. [2, 3, 4, 5] In developed countries, a skewed age structure is expected to drive the dramatic increase in national healthcare costs down to predictive, preventive, participatory, and personalized healthcare. [2]

Despite looking at the literature and prior studies to identify a holistic approach to health forecasting, it has not been attempted in any of the existing studies to our knowledge. We further identify the various components and potential data sources which can be integrated into the macro context to augment the preventive healthcare regime. We propose a conceptual blueprint as a tool wherein Unique Health ID (UHID) can be connected to multiple data sources, as well as to predictive health analytics, which can support a preventive healthcare management strategy. Finally, this paper discusses the broader gaps that practitioners should explore in this field.

RELATED WORK

A forecast is a prediction that is made by using a systematic process or intuition to acquire foreknowledge about future events. [6] A wide range of forecasting literature discusses two approaches, statistical and judgmental. [7, 8]

Health forecasting involves the prediction and forewarning of conditions or episodes of disease and facilitates public health planning and preventive medicine in populations. [9, 10] Soyiri and colleagues [11] mention in their study that health forecasting can be done using data from population health surveillance, such as demographic and health surveillance and epidemiological studies. As a result of a reliable health forecast, health services can be delivered more effectively,

(1) by improving preventive health care/services;
(2) by creating alerts for patient overflows (during peak healthcare demand); and
(3) by significantly lowering the cost of supplies and staff redundancy.

The impact of health forecasting on health conditions such as ischaemic heart disease [12], chronic obstructive pulmonary disease [13], diabetes incidence [14], and emergency department visits [15] has been studied in some previous studies. When explored, the earlier studies have focused on the predictions employed for the intended and actual hospital stay, vulnerable and susceptible to diseases and relapses, and complications.

Azari and colleagues [16] propose a multi-tiered data mining approach for predicting the length of stay at a hospital. Based on k-means clustering, the authors identified ten different classifiers and performed classification on groups of similar claims for the hospital stay. For varying levels of clustering, the authors evaluate and rank the classifiers using a combined measure of performance. When clustering is used as a precursor to forming the training set, better predictions are obtained than when non-clustering is used. Additionally, the authors found that the accuracy of the projection of individual patient length of stay was consistently higher than those reported in the literature. A total of five methodologies were proposed by Gustafson [17] to predict hospital length of stay. Two of these methodologies generated point estimates based on surgeons' subjective judgments, and the other three were Bayesian distribution estimators, which were developed based on empirical data and subjective assessments.

By reducing the need for radical treatments like surgery and chemotherapy, preventive healthcare programs can save lives and improve quality of life. There are several preventive services that are well-known, such as flu shots, blood tests, and mammograms. For over three decades, preventive healthcare programs have been recognized for their substantial savings in diagnostic and therapeutic costs and lower capital investments. [18] Women between 50 and 69 years can avoid up to 40% of breast cancer deaths by having regular mammograms. According to Gornick and colleagues [19], 36% of patients without screening mammograms are diagnosed with late-stage breast cancer, compared with 20% in the screening group. The ability to share healthcare data will make everyone smarter, for instance, by being better able to understand patterns and trends in public health and disease to improve the quality of care [20]; by providing better recommendations for exercise and physicians [21]; by planning services that maximize the limited national health service budgets for everyone's wellbeing. The raw data from multiple platforms can be blended together to form meaningful data, i.e., to analyze and predict diseases and illnesses in the future. [22]

Guo and colleagues [23] mention in their study that to accurately forecast the epidemic of HIV/AIDS in China, it is crucial that the HIV transmission dynamics are analyzed in high-risk populations, the number of HIV-infected individuals who are not identified, and newly acquired HIV-infected individuals should be estimated, and government prevention and control programs should be evaluated. In order to gauge the effectiveness of Chinese Government prevention and control programs, they calculated the number of unidentified and newly acquired HIV-infected individuals each year. In an analysis by [24], longitudinal data from a commonly worn commercial wearable device (Apple Watch) could assist in diagnosing and identifying symptoms of COVID-19. This metric predicts COVID-19 infection before nasal swab polymerase chain reaction testing. Therefore, HRV can be used to identify COVID-19 infection before polymerase chain reaction testing is performed.

The role of information in health care is well acknowledged. [25] Information and technology are becoming increasingly crucial in strategies for preventing, managing,

and predicting health problems. [4, 5, 25] Throughout the foreseeable future, the world of the economy is going through a dramatic and fundamental shift due to the digitization of health and patient data. A number of factors are driving this shift, such as the aging population, lifestyle changes, the proliferation of mobile devices and software applications, innovative treatments, and the increased focus on care quality and value. Ultimately, this will help promote clinical decision-making, improve healthcare delivery, management, and policy-making, analyze diseases, monitor adverse events, and optimize treatment of many illnesses. [26] With minimal performance degradation during prospective validation, Ren and colleagues [27] accurately predicted postoperative complications using automated real-time EHR data, with accuracy that matched surgeons' predictions and minimal performance degradation during prospective validation. Random forest architectures, which accurately represent complex nonlinear associations among features, were used to optimize the predictive performance. Mobile device applications were provided with model outputs to facilitate integration into clinical workflows. As far as their knowledge goes, this system is the only one that accurately and automatically acquires data and displays it on mobile devices in real time.

NATIONAL INITIATIVE - NDHE

A Committee constituted by the Indian Ministry of Health and Family Welfare identified the need to create a National Digital Health Ecosystem (NDHE) that is not a system but an ecosystem. [28] In addition to providing an architectural vision, the National Digital Health Blueprint (NDHB) also guides its implementation. To drive the implementation of the Blueprint and promote and facilitate the evolution of NDHE, the NDHB recognizes the need to establish a specialized organization, the National Digital Health Mission (NDHM). [28] As illustrated in Figure 1, they created a federated architecture which consists of five layers of architectural building blocks, a set of architectural principles, a federated architecture, privacy and consent management, national portability, an EHR, the application of standards and regulations, health analytics, and, above all, multiple access channels, such as call centers, the India Digital Health portal, and the MyHealth app. [28]

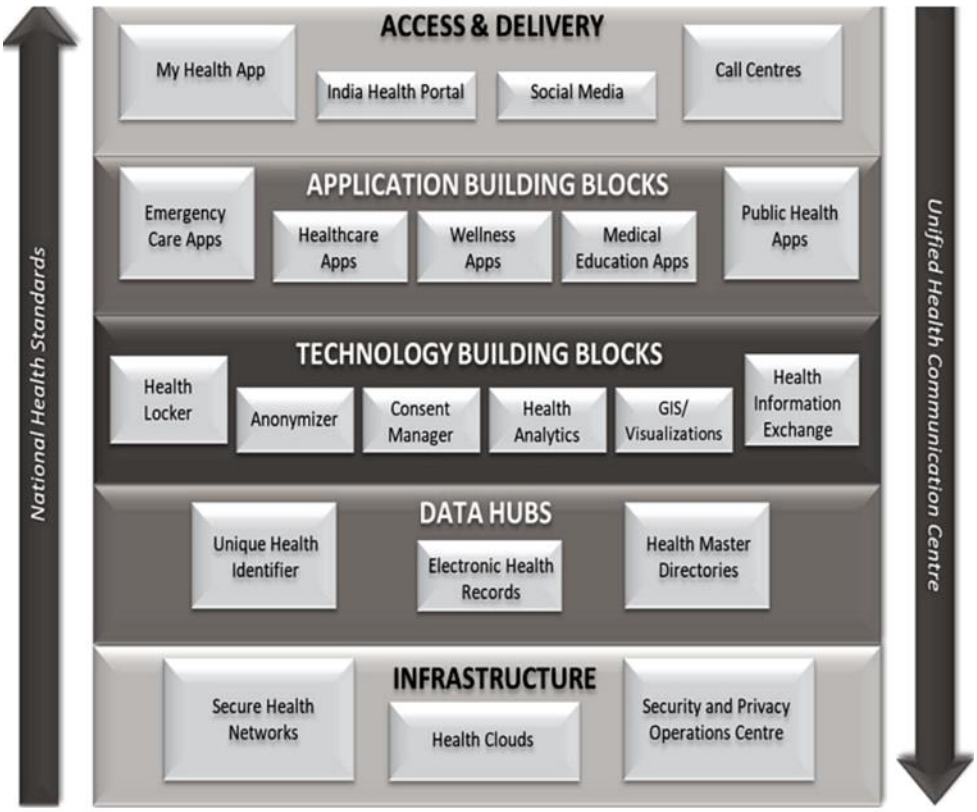
The federated architecture proposed by the Committee is characterized by the following features:

- The architecture consists of three levels: national, state, and regional, as well as facility-level.
- On each level, four layers of building blocks are designed, each representing a particular type of building block, such as Infrastructure, Data, Technology, and Application.
- Layers, levels, and building blocks are loosely coupled using standardized APIs and a 'Need to Connect' approach.
- Building blocks are designed with minimality at every level and layer.
- Data consistency, interoperability, and national portability can be ensured by developing, maintaining, and securing a minimal number of data building blocks.
- There is no national database of health records for citizens.

State health records are only maintained in the form of indexes, pointers, or links.

The Blueprint also mentions that Unique Health Identifiers (UHIDs) are required in the health domain to identify persons, authenticate them, and connect their medical records across multiple systems. The UHID contains demographic information such as name, father's/mother's/spouse's name, date of birth/age, gender, mobile number, authentication route, email address, location, family ID, and photograph, following FHIR's person resource definition. UHIDs must be unique, and the algorithm that issues a UHID must attempt to return the same identifier for every individual. For designing the structure and processes related to UHID, existing multiple identifiers like Aadhaar, PAN cards, Ration Cards, and Electors Photo Identity Cards (EPICs) may be incorporated, subject to regulatory compliance. A standard for exchanging healthcare information electronically is Fast Healthcare Interoperability Resources (FHIR). [28] The adoption of FHIR ensures access, discoverability, understanding, and standardization of electronic health records to facilitate automated clinical decision support.

FIGURE 1: BUILDING BLOCKS OF NDHB



Source: Ministry of Health and Family Welfare. [28]

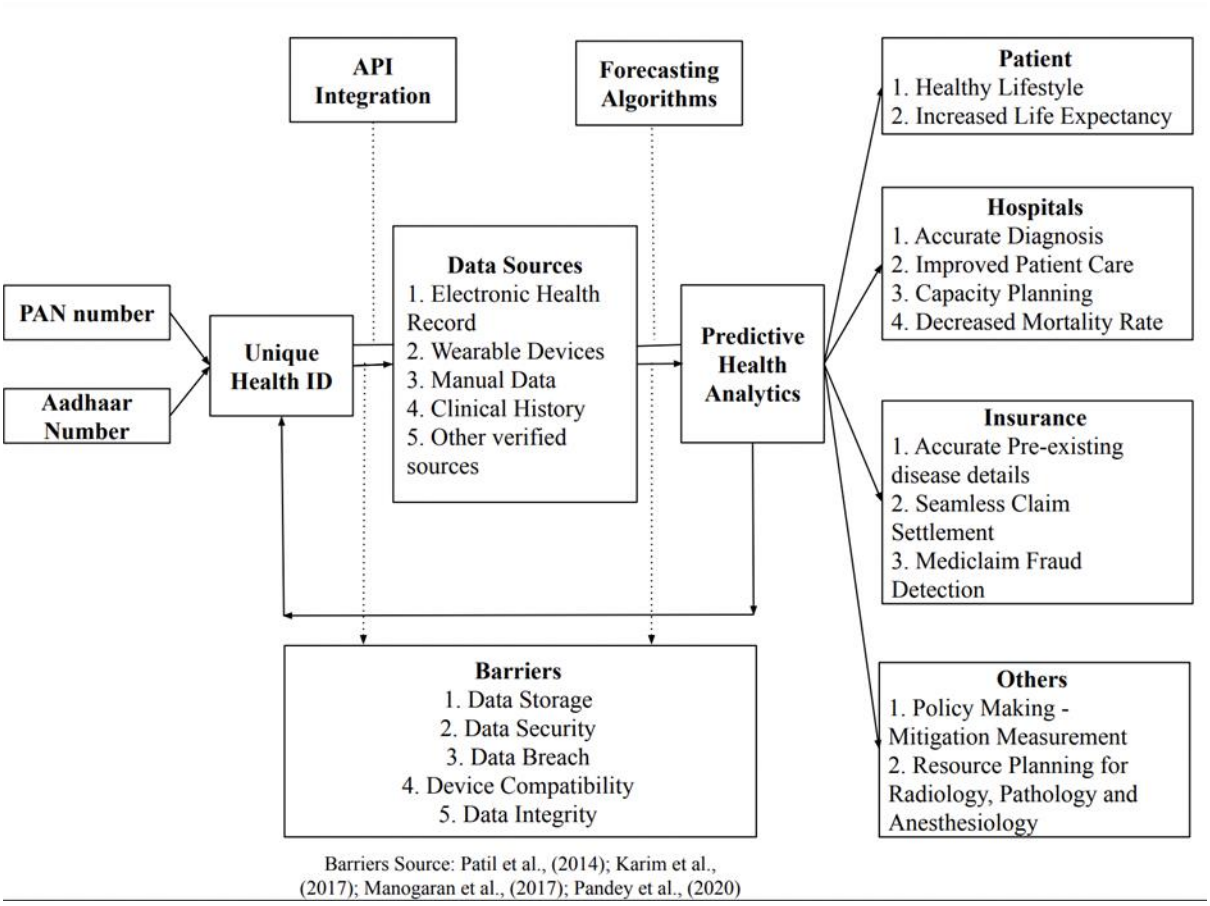
It is evident from the federated architecture proposed by the MoHFW, the components of the NDHB outlined above, and the extensive literature on illness prediction that the mainstream literature accepts the research area. As mentioned, the literature discussed above emphasizes the use of data and technology to predict one disease, whereas the Blueprint emphasizes the use of the Unique Health Identifier (UHID) as well as integrating healthcare as an ecosystem. The authors, through this research, however, propose the extended functionality of the healthcare ecosystem, such as UHID, and individual research on predicting specific diseases using the EHR and other medical information will be expanded and integrated, helping not only to indicate any particular disease but also to predict one's overall health.

THE PROPOSED TOOL

To predict and prevent illnesses, improve patient care and treatment, and reduce disease burden by providing timely and assistive recommendations, the proposed healthcare tool integrates various types of EHR data, sensory data, and user input data throughout the day. Data from structured, unstructured, and graph types are integrated with the system to predict diseases. As illustrated in Figure 2, as a data source, the wearable device can provide the system with information about movements, heart rate, sleep rate, insomnia levels, blood oxygen, blood pressure, temperature, food intake, calories burnt, blood levels, and more. Environmental and behavioral factors also contribute to several diseases studied by epidemiology. To understand disease onset, development, and care in diverse populations, it is necessary to know how these factors interact. As a second source of data, the user is asked, individually with the help of their smartphone, about their current treatments, drugs, habits, daily meals, weight, height, previous diseases, existing diseases, genetic problems, food allergies, family histories of disorders, where they live, what is the most common disease in their area, and how they live their life. In combination with UHID, the above functionality will work as a unique health profile that can be accessed at any time by any stakeholder in the ecosystem. Using multiple machine learning algorithms, the health profile will be analyzed for predictive and prescriptive information. As a result, users can forecast their health status, resulting in a healthier lifestyle. Increased life expectancy is also a result of a healthier lifestyle. Healthier lifestyles are associated with lower risks of cancer, cardiovascular disease, diabetes, and mortality, along with longer life expectancies and fewer years living with these diseases. [29] According to [29], promoting a healthy lifestyle will reduce healthcare costs reducing the risk of developing chronic diseases, such as cancer, cardiovascular disease, and diabetes, and by extending the life expectancy of disease-free patients.

According to Lutz and colleagues [30], infectious disease forecasts can be used for more than just communication in seasonal and emergencies. They also mention that the health care providers (including hospitals) could use forecasts to inform their treatment decisions (for example, antiviral treatment for influenza patients). The forecasts could also be used to guide the allocation and deployment of human resources and treatment inventory in preparation for surge capacity and hospital resource management.

FIGURE 2: BLUEPRINT OF THE PROPOSED TOOL



Source: Barriers [31, 32, 33, 34]

In order to validate the tool and get feedback, we discussed the proposed tool's functionality within our network. The following steps were used to explain the prototype of the tool to 32 participants based on the convenience of the authors.

1. KYC Verification for creating Unique Health ID
2. Sync existing data from all devices, i.e., health tracker apps, fitness tracking devices, oximeters, etc.
3. Manually add critical information, such as personal history, family history, previous reports, medicine allergies, food allergies, etc.
4. The user can move back and forth to edit and make changes as needed, e.g., Day wise changes in weight, sleep, water intake, food intake, heart rate, etc.

The tool would allow users to see what diseases they might face during their lifetime with a button click. The timelines will also be easier to predict for more informed users for example, weight gain within the next five years. When verbally discussed with 32 participants, the basic functionality described above was enthusiastically accepted. The literature suggests that this is feasible, even though respondents were unsure whether it would happen in practice. Moreover, respondents reported spending much time and money on their health after the pandemic. The tool would help them schedule preventative appointments with their doctors, preventing diseases or making them easier to treat.

USE CASE

It was requested by the participants in our study that we describe how the usual use case would feel. Responding to which we believed that the readers would also have a similar concern. We describe in this section how the proposed tool can be useful and functional in two scenarios, one for a hospital visit and one for a private clinic visit.

Visiting a hospital:

In a Hospital Information System (HIS), every patient who has visited this specific hospital at least once has their personal and medical information stored in a central database. In the outpatient department, a patient presents their UHID when entering the hospital so the database can be updated with the date and reason for the visit. In addition, a check whether any new information stored in the cloud by private doctors or other hospitals will need to be updated offline in the patient's electronic medical record, which is maintained by the HIS. Afterward, the patient will be referred to a doctor who can address their problem. By using the HIS, the doctor can access the patient's current medical record during the consultation. Once the doctor has completed the consultation or clinical examination, the HIS will be updated with all documentation regarding the diagnosis and any suggested treatment.

Visiting a Private Doctor:

Similar to the previous scenario, if a patient visits a private doctor and the doctor has the necessary technical infrastructure (software and hardware), and the patient authorizes them, the doctor can retrieve and update the patient's medical records by entering the patient's PIN to access the information stored on their tool. With every new medical history that is saved in the tool, the date of the visit and medical identification number will be included.

DISCUSSION AND CONCLUSION

With a large number of hardware and software configurations available in the market, especially for the Android platform, app developers must produce a highly compatible app. Testing an app's compatibility can be performed on a subset of devices that adequately covers the characteristics of devices that users are likely to use. Being up to date on API building trends is key to developing a flawless integration module.

Due to the fact that APIs work in tandem with web-based programs, attacks are possible on these technologies. An unprotected or unencrypted database can be easily accessed. It is essential to consider potential security breaches when integrating APIs. In order to forecast health, it is necessary to update current information regularly using novel techniques and data while considering the principles of health forecasting. By using time series analysis or other probabilistic methods, health forecasting can exploit patterns in health data. Enhanced and improved health services can be achieved through health forecasting, but it also has a number of shortcomings due to its data sources, methods, and technologies. In order to facilitate the delivery of healthcare and health services, the proposed tool aims to stimulate further discussion on standardizing health forecasting approaches and methods. The integrity of data remains a critical concern for the healthcare industry as well. There are a number of potentially serious consequences that may result from data integrity breaches in healthcare institutions. In today's healthcare environment, cyberattacks are increasingly perceived as the gravest threat. The complexity of a healthcare institutions' organizational structures, as well as regulatory pressures, makes preserving data integrity a challenge.

The impact of such a tool on the quality and efficiency of health care services has not yet been evaluated in a large-scale implementation, but there are indications that it may have a substantial impact. In addition, it will enhance flexibility and interoperability and streamline the administrative and functional processes of healthcare organizations. In order for the medical record to be stored in the cloud, a standard structure for the medical record must be agreed upon and ensure compatibility between the various applications. The memory structure of the tool, both in terms of access attributes and size, must also follow predetermined guidelines. Pharmacy, pathology, medical insurance, and other health-related activities can easily be added to the proposed system.

MANAGERIAL IMPLICATIONS AND LIMITATIONS

Data accuracy remains the most critical aspect for this tool. Numerous fitness tracking watches and devices are already available for the general public. Most users, however, struggle with their accuracy. They often display different readings on the same device. Another concern is the security of the data. In a world where cyber security issues and data leakage issues often arise, maintaining technical boundaries for such a product should be of paramount importance. Practitioners and managers working in this direction must also consider compatibility issues when integrating the tool with existing devices at this level. We also suggest that any cross-validation strategy should be evaluated case by case. Currently, there are no standard scales for validating a health forecast based on a particular forecasting horizon. In order to streamline and refine the process of validating health-forecasting models, further research is necessary. It requires extensive research and critical design thinking to understand how the predictive tool can accurately predict health and wellness; thus, results drawn from the study should be viewed with caution.

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CONFLICT OF INTEREST:

No potential conflict of interest was reported by the authors.

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