Data Analysis Models For Optimizing Telemedicine Platforms In Rural Healthcare Settings

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Abstract

In an era where an increasing number of companies operate using data and information management systems that monitor and ensure appropriate telecommunication systems and speeds, through well-related hospitals and registered personnel, what is said to be good healthcare delivery, rural healthcare has maintained its remarkable status. Commissioners of healthcare services rate lower for quality services, chronic disease conditions persist, a disparity exists, and physicians are lower in number to adequately handle the gap in delivering services. This paper focuses on technology knowledge and data analysis to situate parameters that help optimize telemedicine platforms to better contribute to closing the gap in rural healthcare settings. Prioritized variables are worthy of discussion. Incorporated data relative to the rural healthcare setting is utilized to model data that is analyzed, interpreted, and formulated recommendations fit for the optimization of the telemedicine platform for eventual usage among the available number of rural consumer groups reachable even as the projects move from the pilot stage. The descriptive, predictive, and prescriptive data analysis model utilized produces a fit recommendation that increases the odds of better healthcare delivery; not just delivery but good quality delivery. Details are documented in the body of the paper.

Keywords: *Data Management, Information Systems, Telecommunication Systems, Healthcare Delivery, Rural Healthcare, Chronic Disease, Disparity, Physicians, Telemedicine Platforms, Technology Knowledge, Data Analysis, Healthcare Optimization, Rural Healthcare Settings, Predictive Analytics, Prescriptive Analytics, Descriptive Analytics, Data Modeling, Healthcare Recommendations, Quality Healthcare, Rural Consumer Groups.*

1. Introduction

Pursuing equitable and quality healthcare delivery in Ghana remains an unresolved international development agenda. The low density of healthcare facilities in the predominantly rural country limits access to quality healthcare and has consistently led to enormous health disparities. In addition, there is a preponderance of out-of-pocket funding; and limited use of healthcare services, especially by very poor people in rural and hard-to-reach areas. Inadequate specialists, low motivation of healthcare professionals, under-equipped health facilities, and insufficient and poor road network systems further compound the sorry state of the healthcare delivery system in Ghana.

Ghana boasts several e-services including e-education, digital financial services, e-business, and e-government services, among others. In the healthcare sector, interoperability seems to be the trend, with the Ministry of Health implementing or in the process of implementing several health technologies that are interoperable. The District Health Information Management System II serves as the primary data visualization tool for the Ghana Health Service. Individual health facilities that upload data to the web platform include community-based health planning and services, sub-districts, district hospitals, clinics, polyclinics, and various teaching hospitals, among others. The District Health Information Management System II is anchored on the use of bar-coded family folders, an electronic medical record with the patient in focus, and relies on chargeable desktop client-server technology that is used by trained professionals. Despite the use of these technologies, inadequate healthcare delivery persists in rural and hard-to-reach areas. Causal evidence from some rural, deprived communities also suggests vibrant informal home interventions. In this paper, we argue that the possibility of mHealth in general, and telemedicine, in particular, is yet to be exploited and that the well-known and popular models of data analysis are capable of providing empirical evidence of the immense benefits that can accrue to Ghana and its people when a telemedicine strategy is pursued.

Fig 1 : Custom Telemedicine in Rural Areas

1.1. Background and Significance

The accessibility of healthcare services is fundamental in protecting and improving the health of people living in medically underserved communities, including rural areas, where residents face numerous health disparities compared to those living in urban areas. Telemedicine has been promoted as a strategy to deliver critical healthcare services in rural areas by providing care remotely using innovative internet and telecommunication technologies. Numerous telemedicine platforms have been introduced to provide critical healthcare services, many of which have been utilized to address immediate stakeholder needs. Unfortunately, mechanisms that systematically link performance metrics to improvements in telemedicine platform design, utilization, and stakeholder satisfaction have not been developed, particularly for healthcare services delivered to rural residents. The long-term objective of this project is to foster policy, health system, care management, and technology ecosystem design changes that dramatically enhance the accessibility and quality of healthcare provided to rural residents.

The short-term objective of this project was to collect utilization metrics from three distinct telemedicine platforms deployed to rural healthcare clinics and to use the collected data to develop a data analysis model that links telemedicine platform performance with telemedicine platform architecture and healthcare outcomes. Given the current state of understanding of telemedicine service improvement, we conducted a review of telemedicine platform performance metrics and then developed a series of reflexive performance projects that were supported by vendor engagement. The manuscript is organized in such a way that our approach, solution, and comparison results are laid out in the next section, followed by the model and hypotheses development section, and the data collection process. Afterward, we go into the empirical methodology that tested our hypotheses before discussing our findings. We summarize our findings, followed by the limitations of the study and the implications for future research, research and practice in the field, and the conclusion.

1.2. Research Objectives

This study aims to develop a data analysis model that can optimize telemedicine platforms by balancing efficiency and fairness, as well as to propose a decision support tool to guide improving the efficiency and fairness of telemedicine platforms. To fulfill the research objective, four studies are expected to be conducted. In Study I, frontier decomposition analysis models will be developed to optimize the efficiency and fairness of telemedicine platforms. In Study II, decision support tools for the proposed models will be developed, and many telemedicine platforms will be evaluated using real data to demonstrate the applicability of the data analysis models and decision support tools. In Study III, a case study will be conducted to promote telemedicine by improving the efficiency and fairness between and within telemedicine hospitals and between and within disease groups. In the final Study IV, we will explore the factors that may influence the performance of telemedicine delivery, including the semi-structured interview, focus group discussion, observation, and questionnaire survey.

Two sub-objectives have been identified for Study I, aiming to develop the data analysis models and decision support tool respectively. For the first sub-objective, we will aim to develop multi-objective fractional programming models to optimize the efficiency and fairness of telemedicine platforms and the corresponding solution algorithm. This focuses on the performance evaluation of telemedicine platforms, as well as the results and improvements of telemedicine services. For the second sub-objective, we will aim to integrate multiple object analysis methods to achieve the optimal solution of the DEA model based on the proposed result and improve guidelines for telemedicine service operation. As a result, a comprehensive and profound evaluation mechanism combining efficiency and fairness indices will be established to enhance the achievement of social responsibility in social services. In addition, new knowledge of who, what, when, and how to approach, improve, and apply the decision support system in practice efficiently and fairly will be achieved.

$$O_h = \alpha \cdot D + \beta \cdot P + \gamma \cdot R$$

Equation 1: Healthcare Delivery Optimization Model

O_h: Optimized healthcare delivery score.

D: Data quality and management metrics.

P: Physician availability and capacity.

R: Rural healthcare resource availability.

α, β, γ: Weights for each factor.

2. Telemedicine in Rural Healthcare

The use of remote patient care in India dates back at least two decades, initially with diagnostic services and later with both diagnostic and consultation services. The level of medical expertise available through telemedicine can vary from consultations conducted mainly by generalist physicians to consultations for specialty care by physicians who provide services that are immediately beneficial to patients. Medical personnel who use telemedicine can also vary, from healthcare providers who primarily receive information to specialists and primary care providers who work with remote practice sites. These service models create unique telemedicine needs, and they also lead to different data that are recorded and transmitted.

Rudimentary consultation services, for example, usually generate only simple radiographs that do not require direct interpretation for diagnosis, but specialization-centric models most often require a full range of diagnostic imaging. Prior experience with telemedicine can affect how healthcare services are subsequently used.

Fig 2 : Telemedicine for healthcare

2.1. Challenges in Rural Healthcare Settings

Rural and urban populations have differences in lifestyle, socioeconomic status, and knowledge. Although rural healthcare settings face unique challenges compared to urban settings, many studies have investigated these themes less than telemedicine technologies. Health technologies are needed to bridge the digital divide and specifically address the unique requirements of rural populations, including the needs of pediatricians working in rural health settings. Telemedicine workflows for rural applications must be efficient and affordable, as healthcare resources must meet the demands of a sparsely distributed population. The platforms developed should cater to the unique challenges of telemedicine use in general and rural areas in particular, such as patient-doctor interaction through this new form of communication, reduced patient monitoring quality, hesitation to adopt new methods of interaction due to concerns about information security, and health service quality issues.

2.2. Benefits of Telemedicine in Rural Areas

Telemedicine presents the enhancement of healthcare without leaving the more rural or remote locations. It will increase rural patients' access to services that would not generally be available without traveling distances of often up to 4 hours. The availability of modern healthcare services in the most rural places has led to the lack of healthcare being referred to as "Medical Desert." Significant upsides to addressing these shortfalls in healthcare currently represent the introduction of telemedicine in rural healthcare systems. These benefits, though, require critical infrastructure for communication and high-bandwidth computers for telemedicine applications such as teleradiology and store-and-forward. These modalities benefit rural hospitals by alleviating the burden of remote healthcare specialists. Mental health includes psychiatry and the psychology of the types of telemedicine performed in rural settings, as reflected in the diagram. The upcoming growth and power of technologies to support people and provide authentic and original encounters in rural healthcare are increasing. Many well-planned telepharmacy programs have been implemented in primary customer groups of rural hospitals. Using videoconferencing, patients, nurses, and doctors in urban areas of the hospital can communicate access to 24/7 confirmations. The monitoring of vital signs and support for senior citizens in their residences in remote areas has engaged in long-distance emergency medical help. Telephone and IVR messages for patients can be very successful with previous medical appointments and proposed healthcare service notifications.

3. Data Analysis in Telemedicine Platforms

Data analysis supported by machine learning and artificial intelligence models can empower telemedicine service providers to develop a competitive edge in terms of internal growth performance, customer satisfaction, and service enhancement. Well-developed models can ensure timely, appropriate, and effective healthcare for people in only a few steps, resulting in their continued trust and reliance. If data analysis and artificial intelligence are acknowledged as important tools to support service innovation for small telemedicine service providers, more providers would allocate greater resources to service platform development, making service-efficient healthcare for remote areas more accessible. This study clarified the significant role of people in developing telemedicine data models, emphasizing external ethical contributions. These central and peripheral community organizations and the various stakeholder group network structures are important to how the data analysis model can be successfully applied to rural telemedicine.

Data analysis plans for telemedicine data models should, as a priority, focus on efforts for service-integrated healthcare for remote areas. It is not only for the subsistence needs of healthcare but can also be an issue where social value is directly shared by the public and private collaborative works. By doing so, the spread initiated by a small number of telemedicine service providers can not only improve the lives of rural residents who are initially isolated on the periphery but also undoubtedly trigger the innovation opportunities of other previously neglected economic development locations. The domain knowledge partnership role is particularly important because it can help the co-created product not only to have technical and operational advances but also to have an impact on future utility. With the role of prior assumptions and biases socializing back and forth, such a domain knowledge partnership and network structure become especially beneficial, as it can broaden ethical participation.

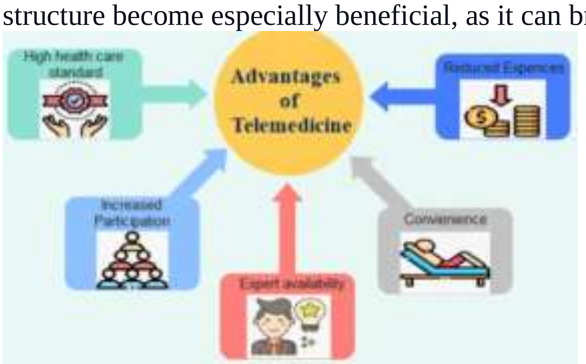

Fig 3 : Advantages of Telemedicine

3.1. Types of Data Collected

In rural telemedicine care, it is essential to collect and analyze multiple types of data, which fall into the following categories: (1) demographic data, (2) patient medical history data, (3) vital sign monitoring data, (4) physical examination data, (5) imaging data, (6) specialist consultation healthcare service data, (7) treatment response data, (8) medication and prescription data, and (9) healthcare cost data. Such data can be captured from various telemedicine platforms or diagnostic devices and services during healthcare delivery. Data recorded from patients seeking service include patient demographic data (age, gender, geographical location, zip code of residence, educational level, occupation, race, income level, and insurance status), insurance carrier type, medical history, previous treatment history data, prior hospital admission data, hospital length of stay data, and top ten healthcare cost groupings. Data recorded during telemedicine healthcare service delivery include: specialist teleconsultation healthcare visit data, vital sign testing data, physical examination data, specialist examination data, treatment schedule modifications, treatment response medical record data, treatment note data, coding level data based on electronic medical record note content, real-time phone call meeting data, treatment plan updates, medication update data, prescription ordering addition data, prescription ordering request completion data, healthcare cost data, and patient care consultation notes.

Since telemedicine service provided by a specialist is billable to an insurance carrier, it is paramount to collect and maintain accurate data related to healthcare costs for the insured member. For this study, medical cost data were obtained from the telemedicine cost center. The leverage of the telemedicine healthcare data collected includes: (1) data analysis for strategic and operational planning and decision making; (2) performance and operational benchmarking with other telemedicine providers; (3) patient profiling for treatment response and effectiveness; (4) provider profiling; (5) outcome research; and (6) evaluation of cost containment efforts. When analyzed and interpreted correctly, the data proves to be useful for clinical practice improvement, education, and service delivery enhancement.

3.2. Importance of Data Analysis

The importance and ubiquity of data in areas of rural health care not only stimulate users to reuse the results of the benchmarking process but also require a response to the question of how to properly quantify the fundamental characteristics of data and existing knowledge. The answer to this question underlies the resistance against the misuse of data, adds a dimension to the conventional concept of statistical criteria for ranking quality, and adds flexibility to the methodological tools used. The primary role of data consists of the capability to correctly measure the parameters and rank them by decreasing importance. In analyzing the results of these parameters, however, the analyst may be interested in more than one dimension of data. Empirically, the debate usually arises in a multi-criteria benchmarking with dependence on perspectives related to the characteristics of the tracking errors of the modeling space. When planners use an index, they are implicitly conducting an exercise in multi-criteria decision analysis on data that has been managed, weighted, and axiomatically adjusted according to areas of analytic concern. As with the selection of any comparative yardstick in performance evaluation, the methods surrounding the use of league tables are a critically complex issue.

4. Data Analysis Models for Telemedicine Optimization

Data Analysis Models for Telemedicine Optimization

The rapid increase in population, coupled with the rising elderly population, has led to an increase in the prevalence of many chronic diseases and a shortage of experienced medical specialists. As a result, telemedicine, a successful and optimistic innovation, has emerged in the field of healthcare and is gradually being considered an obtainable choice for efficient and sophisticated healthcare. With the improvement of telecommunication and information technology, telemedicine, as a new form of medical care delivery, leverages various telecommunications and electronic information tools to provide a comprehensive and cost-effective form of healthcare delivery. Tremendous development is currently occurring in telemedicine. In 2009, an estimated 400,000 patients used tele monitored home-care services, and the number is estimated to reach 2.1 million across the United States.

The typical telemedicine systems are categorized into three main types: real-time or live two-way video and audio, store-and-forward technology, and remote monitoring. A typical telemedicine platform comprises healthcare providers and facilitators. The providers are usually expert healthcare professionals, such as physicians, nurses, and dietitians, who deliver medical advice and healthcare services, including diagnosis, treatment, consultations, prevention education, management, and follow-up on the telemedicine applications. The facilitators are the group integrating multiple physical devices with telecommunication technology and systems to enable the operation of the telemedicine platforms. They are responsible for patient administration, technical support, and system management. Telemedicine systems have made significant changes in rural healthcare settings. In this paper, we mainly focus on the store-and-forward type of telemedicine service for chronic wound care, which is a very time-consuming and expensive service in traditional medical administration.

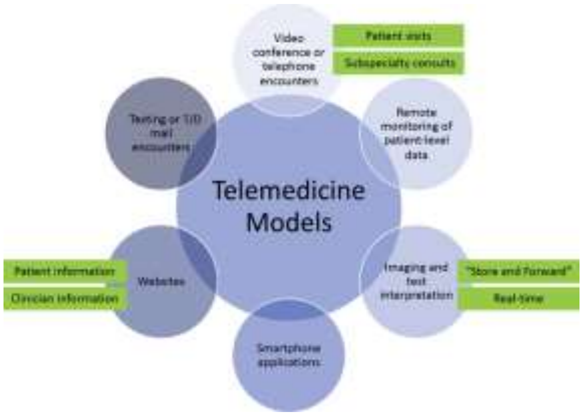

Fig 4 : Telemedicine in Obstetrics

4.1. Descriptive Analytics

Before applying predictive models to our dataset, we conducted descriptive analytics. Descriptive analytics help to understand the structure of our data and to answer "what has happened?" This in turn will help to identify patterns and trends within our data. Descriptive statistics can also be used to compare our data's structure against known parameters of the population we are studying, such as the variance or mean. Therefore, we start the analysis by examining the underlying structure and characteristics of our dataset. We began by looking at the data for problems such as "entries missing," "entries of the wrong data type," and "incomplete information." We started with descriptive statistics to understand our data. We ran a frequency analysis for categorical variables, and a mean, standard deviation, min, max, and range for numerical variables.

We began the descriptive analytics for our dataset by exploring the following questions: How many rural health workers are in the dataset? Where do they work? And how many online consultations took place? In our model, the dependent variable is "the rural health worker use of a telemedicine platform for online consultation," and the independent variable is "supervisor follow-up." We will first conduct a description of the dataset under these variables and then proceed with the model-building process.

$$U_s = \frac{1}{1 + \exp(-(\sum_{i=1}^{n} w_i x_i + b))}$$

Equation 2: Predictive Model for Service Utilization

U_s: Predicted service utilization rate.

x_i: Features such as patient demographics, chronic conditions.

w_i: Weights for each feature x_i.

b: Bias term.

$\exp$: Exponential function.

4.2. Predictive Analytics

Predictive analytics refers to a group of techniques that are used to predict the future behavior of data. Predictive analysis is applied to data that is static and is used to study and model data. The models derived from predictive analytics can be applied to future scenarios. Typically, predictive models in healthcare are used to answer individual patient questions. This can be a question such as: "What is the probability of patient readmissions?" or "What is that patient's risk of postoperative infection?" It attempts to address a "what" question and is useful when there is a well-defined dependent variable. The main goals of modeling a healthcare problem in a supervised manner are to characterize the input and output relationships, to study and interpret the available data for a better understanding of the relationship, and to provide insights to guide clinical care decisions.

There is a need to understand the potential impact of telemedicine interventions on the population health in question, and the key is to have good predictive models. In the context of telemedicine platforms, predictive analysis models are typically built on historical telemedicine and/or telemedicine non-sensitive data along with patient data related to their chronic diseases. Most models apply supervised machine learning and deep learning algorithms to extract the latent patient features related to potential health outcomes from data sets, and then use the trained models to predict future patient outcomes. Modern analytics processes and technologies are steadily driving advancements in healthcare technology. In particular, modern telemedicine applications are evolving rapidly, so that providers of telemedicine health services can now supervise care for many kinds of patients over long distances.

4.3. Prescriptive Analytics

Prescriptive analytics is an emerging field of analytical methods designed to answer questions such as "What should you do now?" The use of these models is not only recent, but current theories relate to the first applications in the field of engineering. These proposed actions come from two types of models: internal and external. Internal models are those utilized to suggest actions supported by their identification of patterns. Conversely, external models follow a normative line that considers different propositions of a legislative and operational nature to be addressed when tackling public policy. The main goal of these models is to reveal relationships that allow the healthcare provider to have a broader idea of decision-making, which can be risky, allowing the redirection of decision-making to more rational and predictive solutions. These models are solutions for representing data availability to support the basis for estimating value in practice.

The concept of algorithms scheduled for the construction of these models originates in statistics and economic theory. The main point guided is weightings that aim to minimize the government's degree of error when making a decision. The significance of the variables is approached from the machine learning method, guiding a more general line on the effects of the predetermined weightings for the models over the governmental decision-making process. These metrics confirm the explanation for establishing an explorative study with the rural healthcare policies related to hospitalization and emergency services to improve health promotion strategies in those communities. The results from the proposed perspective declared positive feedback for guiding politicians in decisions related to this theme, indicating how to invest in this area, and preparing communities for the effective activation of public medical and hospital services according to the locality's demand.

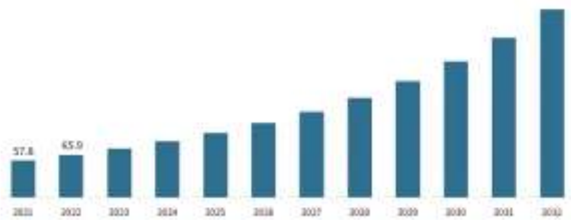

Fig 5 : Telemedicine Market Share – Growth Report, 2032

5. Case Studies and Applications

In this section, we discuss the case studies and practical applications of the machine learning and data analysis methods presented in the previous sections. We begin with the problem of reducing the time spent by primary care clinicians in determining and entering clinical diagnoses for their patient visits. As a motivating example, we use a major medical center that sees patients both from inpatient admissions and ambulatory clinics located in the same facility. About half of the inpatient referrals were related to new admissions, and the length of stay for these patients is very short. Most of the new admission statuses were unclear and needed immediate action. Except for the emergency department, the ambulatory clinic notes, such as encounter reasons, floor notes, clinic notes, diagnostics, orders, and click activity, could become useful predictors to indicate the potential new patient admission status or facilitate the triage workflow.

The data available for patients from the clinics over certain time spans combines these notes with the patient length of stay to generate a training dataset. After replacing the missing values in both the activity and documentation data sources, we calculate the Pearson correlation coefficients between the length of stay and the sample distribution filtered by the top activity categories. We carry out a split test on 80 percent and evaluate the ROC area for both data sources, respectively. Our investigation indicated that a hybrid model contains features from both the activity and documentation sources. The clinicians can integrate a large proportion of predicted next activities from both sources. Finally, the results show that more than 76 percent of the projected next patient statuses are either in the potential new patient admission or needed inpatient status.

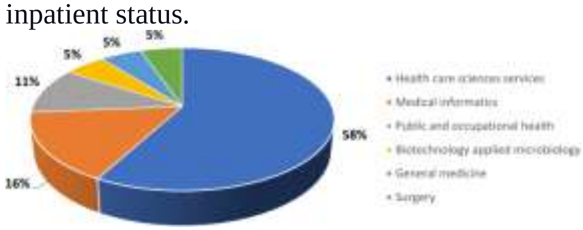

Fig 6 : Telemedicine and e-Health research

5.1. Successful Implementations in Rural Areas

This section examines two telemedicine platforms in a Rural Area Telemedicine Program - Mental Health and Specialty Programs. It then describes a successful implementation of a telemedicine program at a medical center in Wisconsin. The remaining programs utilize telemedicine technologies to remove numerous barriers faced by rural residents in need of healthcare services. The barriers include a shortage of healthcare workers, inadequate financial resources, transportation, and ambulatory limitations. Security, privacy, and protection were the primary issues for the managers implementing and using telemedicine services.

The objective of a Telepsychiatry Project is to quantitatively compare the mental health of patients who travel great distances from their homes to receive services at a university hospital to similar patients who receive their services near their homes through the use of television. Researchers are monitoring the changes in mental health as well as monitoring the costs and the convenience of having telepsychiatry services available close to patients' residences. The monitoring of the effectiveness of telemedicine services will help both the mental health providers and the third-party payers negotiate a mutually beneficial rate for providing mental health to rural residents that is equivalent to or less than the costs associated with servicing urban residents.

5.2. Lessons Learned and Best Practices

This section presents the lessons and best practices that were learned from deploying a telemedicine solution in rural healthcare settings. These best practices relate to the deployment of telemedicine technology within the healthcare setting. The lessons learned from the data analysis models and the use of telemedicine technology are also presented.

5.2.1. Telemedicine System Deployment Best Practices

The lessons learned throughout our telemedicine development and deployments have led to several best practices that are useful for others seeking to develop telemedicine technologies. These include:

1. Secure, continuous internet access is key for successful telemedicine implementations; success would not have been achieved without the costs, commitment, and quality of services provided by various companies.
2. Implementation staff must be able to explain and enforce access policies and procedures to clinic staff, patients, and caregivers.
3. Before implementation, unambiguous departmental responsibilities, hospital usage, and patient referral acceptance criteria should be agreed upon by the hospital or participating clinics.
4. Policies for declining patients in remote locations for both scheduled and walk-in new and existing hospital patients must be established, including setting up a back-channel system. For scheduled visits, clinic staff members must call the appropriate patient registration department in advance.

5.2.2. Best Practices for Data Analysis Models

Data from these original telemedicine clinics continues to be mined looking for all sorts of patterns and trends. Previous work has presented findings using this data, generally in the areas of medical documentation, telemetry, mobile nursing management, and resource utilization. Much of the research is designed to track and justify the success of the telemedicine model itself and to identify possible avenues for improvement. The architecture supports a variety of experimental and observational data that seems useful for diverse telemedicine informatics and operational research applications. However, caution is advised regarding the poor signal quality from telemetry solutions designed decades ago for short-range, in-building use.

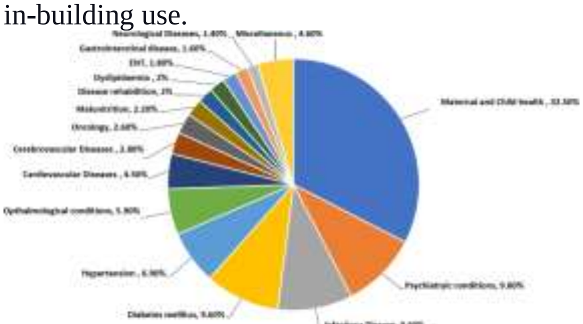

Fig 7 : Telemedicine for improved primary healthcare in India

6. Future Directions and Conclusion

Future Directions. Given that the Internet of Things (IoT) is pushing towards the digitization of health by integrating doctor-patient counseling, health monitoring, action reminders, and environmental supervision devices into the healthcare service system, this provides a vast amount of data for the statistical analyses of telemedicine platforms and contributes further insights for healthcare providers. By identifying a series of suitable parameters, relative data procedures can be designed, which can then perform a healthcare provider's composition, the retrieval of the standard device, the appropriate rate, psychological qualities, and emergency response time from dysfunctional performance. The enormous potential that big data has for giving systematic thought to such issues is currently unaddressed, but it constitutes an extremely important area for future research.

Information asymmetry and the moral hazard of the supply and demand sides of a healthcare services system are two key questions that torment the doctor-patient relationship and have yet to be thoroughly explored from online data through the use of validation and comparison studies. Moreover, with the establishment and continuous improvement of the healthcare service data capital platform, it is clear that the healthcare industry has not yet formed a consensus on how to better realize the efficient value of healthcare big data. If this aspect is combined with the construction of information capital ecosystems, the overall profitability of online healthcare providers can be effectively promoted. In addition, by identifying a comprehensive range of factors, relative regression models can be designed to measure the economic scale and effects of online-offline cooperation between grassroots health service providers and online healthcare platforms. Also, a research implementation roadmap will then be developed to provide a basis for healthcare sector decision-making.

Equation 3: Prescriptive Model for Healthcare Improvement

$$I_h = \sum_{i=1}^{n} (v_i \cdot c_i)$$

I_h: Healthcare improvement index.

v_i: Value or importance of each healthcare factor.

c_i: Change in healthcare metric due to the intervention.

n: Number of factors being evaluated.

6.1. Emerging Trends in Data Analysis for Telemedicine

In this section, we provide an overview of the most common data analysis models used to optimize telemedicine services. We have subdivided the overview into three distinct categories: clinical data, technological data, and public policy modeling. In each subsection, we list the respective attainable outcomes and the associated models or approaches used.

Telemedicine has been around since the introduction of society publications in 1924. However, it is still facing issues involving pricing, regulations, and the distance barrier. Some of the most promising trends that have emerged to become game changers in the field are the maturity of information technologies, the radical increase in the application of information technologies to healthcare problems, and the continued advances in the field of artificial intelligence. Specifically, advances in healthcare data integration, storage and exchange, large-scale omics profiling, precision medicine, clinical and behavioral data analytics, gene therapy, and next-generation diagnostics.

These changes inspire and demand modifications in our healthcare systems to adapt, evolve, and distribute the benefits to a growing society. Not all areas are affected to the same magnitude or at the same time. Additionally, the impact varies among the different stakeholders, such as governments, private organizations, and individual citizens. One area that is poised to gain significantly from these advances is rural healthcare, particularly in specialized areas like telemental health, teledermatology, telecardiology, and teleophthalmology. Currently, these rural telemedicine services are facing structural barriers to offering their services at a patient-friendly cost for both the patient and the healthcare provider. The expected advances in research funding will provide the necessary boost. We are excited about the opportunities that the increasing materialization of these promising trends represents.

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