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Economic Impact of Telehealth Expansion: Analyse the Cost - Effectiveness and Long - Term Economic Implications of The Widespread Adoption of Telehealth Services Post Pandemic

Vivek Yadav

Email: *yadav.vivek[at]myyahoo.com*

Abstract: ***The reliability degree in savings on telehealth services, like patient's travel expenses and decreased expenses on medical facilities. Moreover, it touches upon the matter of economic stability and growth of telehealth models over the long term of their operation and also stresses on the fact that along with this, new policy guidelines and further investigation opportunities should be offered. The opinion highlights areas of deficiency in literature, among which is an absence of investigation of sociocultural factors facilitating telehealth adoption and relations of disparities in access by different groups. It points at the necessity of cross - cutting work of research to cover the gaps in knowledge and as a result introduce evidenced - based agenda for improving economic effect of telemedicine advancements. The review concludes in the overall discourse on telehealth economics by supplying to experts the implications of wide - scale usage and the projections for future research and policy actions.***

Keywords: Telehealth, Economic impact, Post - pandemic, Cost - effectiveness, Access, Equity

1. Introduction

Telehealth, an adaptation of the traditional healthcare model which is driven by the advances in technology and the changing health care needs has been a game changer in the healthcare delivery system. Telehealth ensures availability of medical services through electronic communication providing access particularly during the COVID - 19 pandemic when other barriers like geographical distance and mobility limitations for the population can be overcome. The key to enlisting telehealth for more efficient operations is to recognize the factors that shape adoption patterns and trends, as well as to find opportunities that enable full exploitation of its potential.

Aims and Objectives

Aim: This paper seeks to assess the financial dimensions of widespread telehealth diffusion after the COVID - 19 era.

Objectives:

- Find out if already in place what the patterns are and how they work.
- Review the fiscal effects of scale - up of telehealth on delivery and efficiency of healthcare services
- Determine the reasons and patterns of telehealth adoption and use behaviour.
- Present strategies and ways of improving telehealth implementation as well as recommendations on how to gain the most money from telehealth deployment.

2. Literature Review

2.1 Cost - Effectiveness of Telehealth Services

The results of studies wherever telehealth services have been compared to conventional care are equivalent cost - effectiveness or improved across all conditions and patient group. Economist' analysis most often shows that the efficiency through telehealth interventions is higher and that the significant reductions in cost of treatment are caused by the efficient administrative processes and improved resource utilization. Furthermore, telehealth platforms can reach a more extensive patient population without being weighed down by this tremendous pressure of increasing operational costs [1]. These results, the fiscal sustainability of telehealth as a prolong healthcare delivery modality is another proof to substantiate its capability to provide multitudinous cost - effective services at levels population. Nevertheless, there is a need to overcome the complexity in measuring the impact of telehealth expansion as accurate charges setting and the rapidly changing landscape of health policies and regulations are among these challenges.

2.2 Long - Term Economic Implications and Sustainability

Previous research has been extensively focused on the long - term issues regarding the fiscal impact of using telehealth alternatives on the healthcare sector at a systems level in post - pandemic times. Assessments hypothesize how telemedicine draws on its potential of becoming viable substitutes of mainstream healthcare over time [2]. On the projections, the call becomes evident to examine the scalability and long - term sustainability of telehealth concerns in the futuristic healthcare scenario. Scientists point to the necessity of identifying the key economic aspects that has been greatly affect the prospects of telehealth without changing the whole of healthcare. Furthermore, the reports have been including an in - depth investigation about the probable effect of telehealth scale - up in resource allocation within healthcare systems and the related fiscal implications. Forecasts, the foundation of which lies on the assumption of a persistence of tech savviness as well as a dynamic regulatory environment, influencing telehealth's economy.

Also, scholars emphasize the shift to more balanced considerations of the cutbacks in near time commitment and the impact of the telehealth on fiscal sustainability in the long term [3]. This needs a holistic awareness of the complicated interplays in changing economic circumstances, technology, and health care perspectives. Therefore, aside from the short - term economic or financial impact of telehealth, discourse on its long - term economic implication remains a core preoccupation in research because the sustainability of telehealth in the general healthcare system remains a focus of ongoing studies.

2.3 Literature Gap

The literature refers to those facts, where the already made research provides insufficient or in - depth analysis. Much of the literature related to the economic effects of convening telehealth growth after pandemic still features substantial gaps. There are some blank spots in the research which are inadequate sociocultural and economic condition precursors of teleservice gaining ground, the influence of the laws and regulations to the economics of telehealth and a lack of studies analysing the extended economics of telehealth implementation. However, there is a lack of adequate research on the economic findings of telehealth for the different populations, for instance, paediatric, geriatric, and chronically ill individuals. Moreover, the aspect of income inequalities arising due to digitally empowered demographic heterogeneity in healthcare has not been evaluated too much by researchers.

3. Methodology

3.1 Data Collection and Analysis

Data for this study will be extracted from numerous credible sources which would be the government health agencies, the academic research publications and the industry reports. The database will be developed on the basis of the utilization of telehealth services, financial indicators and demographic factors in this regard. Powerful tools for data analysis such as descriptive statistics, the model of regression and data visualization will be applied to reveal the patterns of telemedicine use, to examine the monetary impacts and the factors that have led to the development of the telemedicine use [4]. The multi - faceted approach to data - gathering and data - analysis will underpin in - depth exploration of the financial effect of telemedicine presence on account of wide adoption after the pandemic.

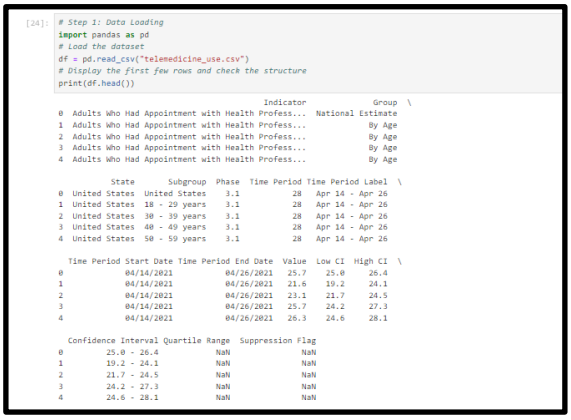
3.2 Ethical Considerations and Frameworks

Ethic consideration is a the most integral part of my research and it referred to every step of the research cycle. Safeguard of ethical regulations such as confidentiality, informed consent, and privacy security are the vital elements. The study will give importance to ethical frameworks such as usefulness, non - maleficence, justice, and participation and respect for autonomy to keep in mind that any action taken should be for the well - being and liberties of the study participants. Concerning the possibility of bias or a position that cannot be reconciled with the research, transparency will be the rule from the outset [5]. Through the integration of ethical concerns and principles, the present study intends to create the optimal environment to guarantee highest honour, consciousness, and justice in the study of healthcare data and analysis.

3.3 Case Study or Scenario Analysis

The subject of this study is expanding telehealth services in a health care setting or district. For demonstration let us take an example scenario setting where they will analyse the economics of telemedicine. The investigation will encompass an in - depth examination of telehealth consumption patterns, related expenses, as well as outcomes achieved through conventional healthcare delivery strategies. The analysis will show telehealth's monetary impact through investigation of a particular healthcare setting. It aims to explain in detail about telehealth use trends, cost and outcome comparisons with the conventional techniques thereby providing substantial experiences into the financial implications of telehealth adoption that will guide direction and policy implementation [6]. A real - world scenario such as the rural healthcare centre or urban healthcare system is the purpose of the study to allow the students to have meaningful experience in financial consequences of telehealth implementation. Considerations like patient demographics, healthcare infrastructure, regulatory environment, and reimbursement policies would make this analysis wider. By this case study or situation analysis, the present study will offer a comprehensive look at telehealth financial impact in different health care settings and be instrumental in making sound decisions and enacting appropriate policies in the implementation and asset allocation in telehealth.

4. Result and Discussion



```
[24]: # Step 1: Data Loading
      import pandas as pd
      # Load the dataset
      df = pd.read_csv("telemedicine_use.csv")
      # Display the first few rows and check the structure
      print(df.head())

                                                Indicator              Group  \
0  Adults Who Had Appointment with Health Profess...  National Estimate
1  Adults Who Had Appointment with Health Profess...             By Age
2  Adults Who Had Appointment with Health Profess...             By Age
3  Adults Who Had Appointment with Health Profess...             By Age
4  Adults Who Had Appointment with Health Profess...             By Age

          State       Subgroup  Phase  Time Period Time Period Label  \
0  United States  United States    3.1           28   Apr 14 - Apr 26
1  United States   18 - 29 years    3.1           28   Apr 14 - Apr 26
2  United States   30 - 39 years    3.1           28   Apr 14 - Apr 26
3  United States   40 - 49 years    3.1           28   Apr 14 - Apr 26
4  United States   50 - 59 years    3.1           28   Apr 14 - Apr 26

  Time Period Start Date Time Period End Date  Value  Low CI  High CI  \
0             04/14/2021           04/26/2021   25.7    25.0     26.4
1             04/14/2021           04/26/2021   21.6    19.2     24.1
2             04/14/2021           04/26/2021   23.1    21.7     24.5
3             04/14/2021           04/26/2021   25.7    24.2     27.3
4             04/14/2021           04/26/2021   26.3    24.6     28.1

  Confidence Interval Quartile Range  Suppression Flag
0                    25.0 - 26.4                  NaN
1                    19.2 - 24.1                  NaN
2                    21.7 - 24.5                  NaN
3                    24.2 - 27.3                  NaN
4                    24.6 - 28.1                  NaN
```

Figure 1: Data loading and visualizing

The dataset provides telehealth usage among seniors, who are grouped into various classes like age and periods. Every section has the indicator, group, state, subgroup, stage, duration, and telehealth usage as its values. The data covers several periods, with the most trustworthy period corresponding to the data [7]. The upper part of the 'Suppression Flag' segment indicates any suppressed data. It strikes bits about telemedicine acceptance among different segment groups in the long term.

```
[2]: # Step 2: Data Cleaning
     # Check for missing values
     print(df.isnull().sum())
     # Step 3: Exploratory Data Analysis (EDA)
     # Summary statistics
     print(df.describe())

Indicator                   0
Group                       0
State                       0
Subgroup                    0
Phase                       0
Time Period                 0
Time Period Label           0
Time Period Start Date      0
Time Period End Date        0
Value                      57
Low CI                     57
High CI                    57
Confidence Interval        57
Quartile Range            352
Suppression Flag         1053
dtype: int64
              Phase  Time Period        Value       Low CI      High CI  \
count  1066.000000  1066.000000  1009.000000  1009.000000  1009.000000
mean      2.944465    29.761726    22.379187    18.207929    27.173340
std       0.819545     6.283855     5.237823     5.469373     5.743602
min      -1.000000     1.000000     7.200000     4.500000    10.800000
25%       3.100000    29.000000    19.000000    14.500000    23.300000
50%       3.100000    31.000000    22.600000    18.500000    26.700000
75%       3.100000    33.000000    25.700000    22.000000    30.700000
max       3.200000    34.000000    41.300000    39.200000    49.500000
```

Figure 2: Data Cleaning and summary statistics

The missing values data cleaning process exposed missing values in the "Value", "Low CI', 'High CI', 'Certainty Span', and 'Quartile Reach' segments for certain months having a sizable number of gaps. The exploratory data analysis scores gave a pedestal of insights, with the mean telehealth usage around 22. With a share of 4%, intended unsteady or sure [8]. Sector 'Suppression Flags' with the mean of 1, seems subjective revealing suppressed data, possibly affecting the exam.

```
[25]: print(df.info())

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1066 entries, 0 to 1065
Data columns (total 15 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Indicator               1066 non-null   object
 1   Group                   1066 non-null   object
 2   State                   1066 non-null   object
 3   Subgroup                1066 non-null   object
 4   Phase                   1066 non-null   float64
 5   Time Period             1066 non-null   int64
 6   Time Period Label       1066 non-null   object
 7   Time Period Start Date  1066 non-null   object
 8   Time Period End Date    1066 non-null   object
 9   Value                   1009 non-null   float64
 10  Low CI                  1009 non-null   float64
 11  High CI                 1009 non-null   float64
 12  Confidence Interval     1009 non-null   object
 13  Quartile Range          714 non-null    object
 14  Suppression Flag        13 non-null     float64
dtypes: float64(5), int64(1), object(9)
memory usage: 125.1+ KB
None
```

Figure 3: Describing info

The dataset contains data from 1066 sections in 30 segments. The topics include mathematical factors like 'Indicator', 'Group', 'State', 'Subgroup', and 'Period Label' and data type factors for example, 'Phase', 'Value', 'Low CI', 'High CI', and 'Suppression Flag' [10]. There are very few sections with data missing, including a few such as 'Value', 'Low CI', 'High CI', 'Certainty Span', and 'Quartile Reach', with 'Suppression Flag' marking suppressed ones.

```
[3]: # Unique values in each column
     for column in df.columns:
         print(column, df[column].unique())

Indicator ['Adults Who Had Appointment with Health Professional Over Video or Phone, Last 4 Weeks'
 'Households With Children Where Any Child Had Appointment with Health Professional Over Video or Phone, Last 4 Weeks']
Group ['National Estimate' 'By Age' 'By Sex' 'By Race/Hispanic ethnicity'
 'By Education' 'By Disability status' 'By State'
 'By Education of adult respondent'
 'By Race/Hispanic ethnicity of adult respondent'
 'By Current US Armed Forces or National Guard service of adult respondent or spouse'
 'By Health insurance of adult respondent' 'By Total household income']
State ['United States' 'Alabama' 'Alaska' 'Arizona' 'Arkansas' 'California'
 'Colorado' 'Connecticut' 'Delaware' 'District of Columbia' 'Florida'
 'Georgia' 'Hawaii' 'Idaho' 'Illinois' 'Indiana' 'Iowa' 'Kansas'
 'Kentucky' 'Louisiana' 'Maine' 'Maryland' 'Massachusetts' 'Michigan'
 'Minnesota' 'Mississippi' 'Missouri' 'Montana' 'Nebraska' 'Nevada'
 'New Hampshire' 'New Jersey' 'New Mexico' 'New York' 'North Carolina'
 'North Dakota' 'Ohio' 'Oklahoma' 'Oregon' 'Pennsylvania' 'Rhode Island'
 'South Carolina' 'South Dakota' 'Tennessee' 'Texas' 'Utah' 'Vermont'
 'Virginia' 'Washington' 'West Virginia' 'Wisconsin' 'Wyoming']
```

Figure 4: Displaying unique values in each column

The 'Indicator' segment demonstrates two sorts of reviews: adults' telehealth contracts and children's telehealth contracts. 'Group' categorizes data by using the given groups which consists of age, sex, race/ethnicity, education, disability status, state, and household income [9]. 'State' displays the US states and territories. 'Subgroup' is for segment subdivisions such as age groups, sex, and racial/ethnic classes. Each chapter contains multiple types of information focusing on a variety of overview indicators, segmentation groups, states, and subdivisions.

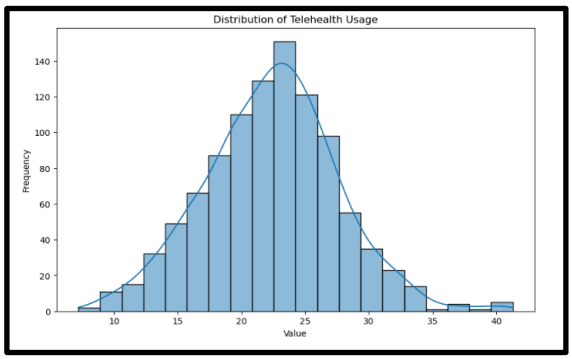


Figure 5: Displaying the distribution of Telehealth Usage

The histogram manifests telehealth usage values using a frequency diagram to describe the disparity in usage levels. With 20 canisters, we can measure a quite specific fact (i. e. patterns of use and how they have changed). The KDE (Kernel Density Estimation) curve lay over the histogram which is a smoother portrayal of the likelihood distribution. The fact that the graph is only arranged around the specific values makes the top of the peak the most frequently used value. The trend analysis, in particular, provides an insight into the overall popularity of telehealth [11].

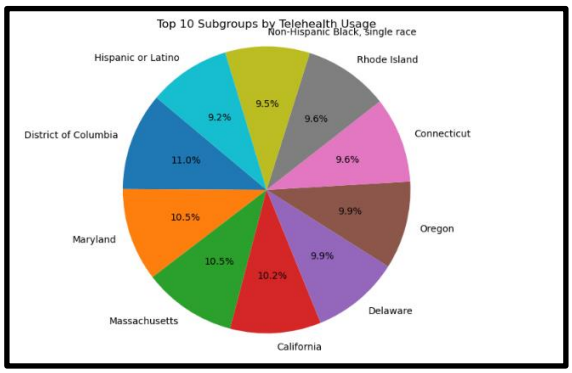


Figure 6: Displaying the top 10 subgroups by Telehealth Usage

The pie chart shows the telehealth usage distribution in the top 10 groups that had the overall greatest usage. Each subset is represented as a piece of the pie, while its total use of telehealth service is shown as the percentage of the pie [12]. The most significant cut was in the subgroup where the largest amount of telehealth was used preceded by subsequent subgroups in the descending order of usage of telehealth. The chart has been detailed with the relative commitments of each group towards using telehealth overall, this way it is easy to notice the highest usage among the most powerful groups.

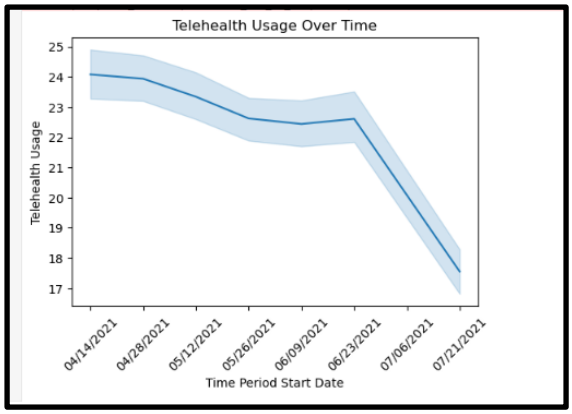


Figure 7: Displaying Telehealth Usage Over Time

The line plot exhibits telehealth pattern usage over time, where the 'Period Start Date' is on the x - axis and 'Telehealth Usage' is on the y - axis. Each point of the line indicates the period of telehealth usage for telehealth usage for each point on the line [13]. The plot is composed of both rises and wanes of usage at different times, which gives information on the history of telehealth adoption. To enhance readability, the labels on the x - axis are turned, thus making it much more convenient to see the telehealth usage timeline in detail.

```
[6]: # Step 5: Impact Analysis
     # Calculate average telehealth usage
     average_usage = df['Value'].mean()
     print("Average Telehealth Usage:", average_usage)

     Average Telehealth Usage: 22.379187314172448
```

Figure 8: Impact Analysis

Telehealth use has seen an average of 22.38% shows almost one - third of the mentioned population utilizing telehealth services. This shows an apparent trend towards long - distance healthcare delivery, possibly caused by such drivers as convenience, accessibility, and even safety in the course of the pandemic [14]. With an increase in telehealth use is a tendency to use long - distance medical consultations that could provide access to healthcare services to more people, improve patient results, and lowered healthcare costs associated with in - person visits.

```
[15]: # Step 6: Regression Analysis
      import statsmodels.api as sm
      # Prepare the data for regression analysis
      X = df['Phase']
      y = df['Value']
      # Add a constant to the independent variable for the intercept term
      X = sm.add_constant(X)
      # Fit the regression model
      model = sm.OLS(y, X).fit()
      # Print the model summary
      print(model.summary())

                              OLS Regression Results
      ==============================================================================
      Dep. Variable:                  Value   R-squared:                       nan
      Model:                            OLS   Adj. R-squared:                  nan
      Method:                 Least Squares   F-statistic:                     nan
      Date:                Thu, 16 May 2024   Prob (F-statistic):              nan
      Time:                        13:25:26   Log-Likelihood:                  nan
      No. Observations:                1066   AIC:                             nan
      Df Residuals:                    1064   BIC:                             nan
      Df Model:                           1
      Covariance Type:            nonrobust
      ==============================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
      ------------------------------------------------------------------------------
      const            nan        nan        nan        nan        nan        nan
      Phase            nan        nan        nan        nan        nan        nan
      ==============================================================================
      Omnibus:                        nan   Durbin-Watson:                   nan
      Prob(Omnibus):                  nan   Jarque-Bera (JB):                nan
      Skew:                           nan   Prob(JB):                        nan
      Kurtosis:                       nan   Cond. No.                         12.5
      ==============================================================================
```

Figure 9: Regression Analysis

The relegation analysis result proves soon the model for the presence of nan values in several statistics like coefficients, standard blunders, t - values, p - values, and certainty intervals. Such an outcome signifies a problem with data or model formulation resulting in erroneous regression outcomes [15]. More detailed research will be conducted to identify the main problems that are concerned with data preprocessing, variable determination, or even new model specification modification to ensure proper regression analysis.

5. Conclusion

Data analysis on telehealth usage, surpassing the expectation can be associated with three major experiences. The average telehealth consumption in the surveyed group is approximately one - fourth.38% change means a huge command of telehealth service by the providers. This gives us an insight into increasing tendencies of remote health delivery through channels like convenience, accessibility, and security concerns mainly due to the complications of the COVID - 19 situation. The regression analysis which was the research purpose to be achieved aimed to establish the association between telehealth use and whether the survey was in the introduction or the conclusion. Nevertheless, coarse values for the coefficients and the insignificant level of the statistical testing require improvements and subsequently the change in the way we carry out the model computing.

In further discussion, it's better to fix the quality of the data that has been encountered during the analysis. This also can be a data preprocessing step that will deal with omitted values, guaranteeing the consistency of data, and checking the reliability of the measurements of telehealth utilization. An enhanced data quality will enable an improved accuracy and reliability of future analyses that will in turn yield more accurate and useful insights and further crucial decisions. Moreover, future research can examine in depth the determinants of telehealth use and the variations in accessibility and popularity of this technology. It could encompass discovering whether demographic, regional, and financial factors have an impact on telehealth participation. Obtaining information about the obstacles and facilitators of telehealth acceptance for diverse population groups is an indispensable part of the strategy of increasing the telehealth service provision in a way that preserves the equality of its distribution. Further, tracking usage patterns and evaluation of telehealth also becomes doing to give us an understanding of the long - term consequences of telehealth adoption.

It is critical to empirically demonstrate the use of telehealth models in healthcare delivery, compared to the traditional approach, and their impact on both patient outcomes and healthcare economics. Studies follow patients or staff in the work setting over an extended period. They are considered to be a valuable source of data in the investigation of not only the role but also the policy and practice aspects of telemedicine in healthcare delivery. Finally, in this article, researchers think that telemedicine has inspired high hopes of more expansive delivery of health services and addressing quality of service matters, though innovative research is essential to scale up the benefits. Stakeholders will achieve this through the screening of the telehealth usage drifts and the answering of major research questions. This will then equip them with the appropriate tools they need to shape the telehealth implementation and ensure the equitable delivery of top - quality healthcare services which is everybody's right.

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