1. **Introduction**

Covid-19 has brought very severe social and economic disruption globally (Chakraborty, et al., 2022). Events of sports, religion, politics, and cultural were highly jeopardized (IASS, 2020).  There were supply shortages leading to panic buying (Arafat, et al., 2020). However, decreased emissions of pollutants and greenhouse gases were observed on positive side (Le Quéré, et al.*,* 2020 *&* Wang, Su, 2020). Approximately 98.5 percent of the world's student population was very badly influenced by the pandemic (**Burgess, Sievertsen, 2020)**. A considerable amount of substandard information about the virus has been circulated through social media and mass media which is mostly found to be backed by bad sentiments (Ahmad, Murad, 2020).

Hospitals faced several challenges due to the Covid-19 pandemic. In the US alone hospitals incurred USD 202.6 billion financial loss (Takaku, et al., 2022). Low and middle-income countries incurred USD 52 billion monthly losses while providing healthcare services to Covid-19 care (Gnugesser, et al, 2022). Most of the loss is attributed to lack of preparation and healthcare facilities around the world (Kaye, 2021). Healthcare staff suffered with a shortage of protective supplies and equipment. Healthcare organizations had to find new strategies to handle pandemic during the first two waves. The notion that healthcare efficiently addressed the pandemic is also firm in certain sections of academia and healthcare industry (Elhadi, 2021 & Sagan, 2020). Despite the facts, it is true that the healthcare industry suffered to a great extent and insufficiently prepared for the pandemic. With these notions this paper seeks to evaluate the impact of healthcare capacity on Covid-19 pandemic.

Immunization or vaccination appeared as another solution for Covid-19 mitigation (Cuadros, et al., 2023) Global level efforts for vaccine development were accelerated during second wave. In the beginning, impact of vaccination was hampered by geographical disparities. Public hesitancy was witnessed in several countries (Sweileh, 2020 & Razai, 2021). This hesitancy was strong in healthcare staff too (Kose, 2021). Vaccination efficacy and its necessity was in question among uninfected sections of public. There was strong feeling in academia and industry that the vaccination may not be a unique solution for mitigation (Moghadas, 2021). The real impact of vaccine through its effectiveness, and capacity was unclear in the beginning. As a result, public strongly believed in nonpharmaceutical solutions such as sanitization, face masking and social distancing (Alagoz, 2021 & Yang, 2022). This research article tries to address this dilemma of vaccine’s efficacy by evaluating the impact of vaccination on Covid-19 mitigation.

1. **Review of Literature**

“Healthcare capacity”, “Immunization” and “Covid-19 pandemic” are study constructs in this research study. While there is abundant literature on Covid-19 pandemic but literature dealing with “healthcare capacity”, “immunization”, and “Covid-19 pandemic” is a severe lacuna. Contents of studies related to Covid-19 pandemic with variegated methods and diverse data sets were provided in this section.

* 1. **Covid-19 Pandemic**

Coronavirus disease 2019, or simply Covid-19, is caused by severe acute respiratory syndrome coronavirus 2 (SARS‑CoV‑2) also a distant variant of the same virus known as Middle East Respiratory Syndrome Coronavirus (MERS-CoV) (CSGICTV*,* 2020). The outbreak was first detected in Wuhan, capital city of Hubei Province in the People's Republic of China, in December 2019 (Wang et al*.,* 2020).  The [World Health Organization](https://en.wikipedia.org/wiki/World_Health_Organization) (WHO) have declared the pandemic as a public health emergency on 30 January 2020 owing to its velocity of prevalence and rate of infection (Rawaf, et al., 2020). Approximately 10 million cases of Covid-19 were reported by 28 June 2020 (Chen, et al., 2020). These cases were observed to be arising from 188 countries and other territories globally (Xu *et al.,* 2020). By June 2020 there were more than 497,000 deaths registered officially on global level (TE, 2020).

The main purpose of this study is to find out cause-and-effect relationships between healthcare facilities or capacity and Covid -19 pandemic. There are very few studies related to similar scenarios in the present body of knowledge. Covid-19 literature is found to be available in two categories. The first category is Covid-19 vs. other factors of study and the second category is other factors of study vs. Covid-19 (McKibbin, Fernando, 2020). Most of the studies are related to the first category i.e., finding the impact of Covid-19 pandemic on other factors such as education, logistics, agriculture, education and many more. All these studies used either infected cases or death rate or both while measuring impact (Davies, et al., 2020). Multiple measures are used to quantify mortality. Death rates vary by region and over time, influenced by healthcare system quality, testing volume, government response, treatment options, duration of outbreak Few studies used measures like population characteristics such as age, sex, and overall health. There are even studies found to be employed by a peculiar measure calculated by using both infected cases and deaths, it is known as “death-to-case ratio” (Gindler, et al., 2004 & Wu, et al., 2020).

* + 1. **Cases & Deaths**

Number of infected cases is one of the observed variables used in this study which represents Covid-19 pandemic. Infected cases, or simply cases, have become an important variable for pandemic measurement (Khanna, et al., 2020 & Gates, 2020). In fact, identifying accurate data related to cases was a great challenge while studying Covid-19 pandemic (Knottnerus, Tugwell, 2020). As much as 2.6 percent of population was tested across the globe as of 24 May 2020 (Wang, et al., 2020). Most of the countries tested only those individuals whose symptoms are apparent but not mild. Coming to results, each country encountered a unique scenario. For instance, preliminary results, in Germany, found that 15 percent of people tested only Gangelt, which later identified as center of potential cluster (Glöckner, et al., 2020). Pregnant women in New York City, and few blood donors in the Netherlands, were also reported to be identified as positive (Vogel, 2020). In China, 13415 confirmed cases and 120 deaths were reported as of March 18, 2020, and Hubei province remained as epicenter of the outbreak (Leung, 2020). India was at high level of risk during first two waves. In fact, the vaccination campaign was hindered by the constant rise of infections besides affecting vaccine production (Chakraborty, 2021).

Cases together with number of deaths were used to study the Covid-19 pandemic in this study. According to protocols, official deaths from Covid-19 generally refers to any person who died after testing Covid-19 positive (Ioannidis, 2021). The recovery rate from Covid-19 is high (Ahmad et al., 2020). However, those who die tend to suffer from the disease for 6 to 41 days, typically about 14 days (Bi, et al., 2020 & Phua, et al., 2020).  Approximately 497,000 people were died as of 28th June 2020 on the globe (Cadell, 2020). As of 3rd August 2023, 72 of 73 countries recorded 81,837,520 confirmed cases and 1,021,658 confirmed deaths (Gavi, 2023). WHO reports 768 983 095 confirmed cases and 6 953 743 confirmed deaths for the same date (WHO, 2023).

* 1. **Healthcare Capacity & Public Immunity**

There is abundant literature related to the impact of “healthcare capacity” on “Covid-19 pandemic”. For instance, Verelst, et al., (2020) considered few variables such as hospital beds, number of physicians, healthcare expenditure and few composite measures calculated by using few formulae. These formulae were computed using parameters related to clinical and non-clinical assets of hospitals. Authors extracted data from a certain online repository named Eurostat.Rajagopalan, Choutagunta, (2020) also used same type of variables in their article while studying “Healthcare Capacity in India”. The article used data related to a few variables such as budgets, hospital bed capacity, and capacity in terms of doctors, nurses, and total healthcare personnel. In this study authors used data from secondary sources such as World Health Organization (WHO), National Statistical Office (NSO) in India. These papers were the same in terms of methods and used secondary data sources. By and large, the research shows positive impact of “Healthcare capacity” on “Covid-19 mitigation”. However, this is just an educated guess which needs affirmation through empirical evidence. This study tries to find such evidence by addressing RQ1.

RQ1: Is it possible to mitigate Covid-19 pandemic through efficient “Healthcare facilities”? Do “Healthcare Capacity” impact “Covid-19 Pandemic”?

Covid-19 immunization is the most gigantic public health action ever happened in the history of pandemics. Shyamsunder, et al., (2023) proposed fractional mathematical model for studying the impact of vaccination on Covid-19 pandemic. The paper suggests scaling up of mass vaccination to reduce the number of unvaccinated infections. Watson (2022) quantified the global impact of the COVID-19 vaccination programs. The article finds that vaccination has certain impact on pandemic, despite inadequate access. Victora (2021) finds that scaling up of vaccination to elderly public was associated with declines in mortality compared to younger individuals. Notarte (2022) performed systematic review and finds that the efficacy of vaccine and its impact is unclear. Loomba et al., (2021) show that misinformation is strongly associated with vaccination decline. Authors also report that this decline is caused by a few socioeconomic factors. Using money as a incentive for the public to get vaccinated is also witnessed a few places (Campos-Mercade, et al., 2021). By and large there is a mixed response to immunization in literature. Few studies attribute Covid-19 mitigation to vaccination and few doubt the efficacy of the same. This study tries to address this dilemma through RQ2.

RQ2: Is it possible to mitigate “Covid-19 pandemic” through efficient practices of “Immunization”? Do “Immunization” impact “Covid-19 pandemic”?

1. **Research Methods**

This study falls in the ambit of causal research. The goal of this study is to evaluate cause-and-effect relationships between study constructs namely “Healthcare capacity”, “Immunization” and “Covid-19 pandemic”. In the literature, most of the articles employed Structural Equation Modeling (SEM) for data analysis. So, SEM identified as a suitable statistical technique for evaluating cause-and-effect relationships.

* 1. **Theoretical Model & Hypotheses**

There are several studies related to modeling of diseases. However, it is difficult to find a precise model for Covid-19 because this disease happened to be a recent phenomenon in the history of pandemics. Mostly there are two types of studies related to Covid-19 in literature. First, impact of the pandemic over study factors such as economy, commerce is abundant (Adnan, Johani, 2023). Second, impact of study factors over disease prevalence. In the first category, the mitigation of a pandemic is being measured by few variables such as infected cases, deaths, denied hospital admission, denied vaccine/antiviral drugs etc. (Tapas, et al., 2008). Second category observed to have depended on variables such as demographic and community features, daily human activities, vaccination, hospitalization, social distancing, and hourly accounting of infection spread (Adiga, et al*.*, 2018; Singh, et al., 2019 & Villela, 2020). Finding a study with factors such as “healthcare capacity”, “immunization” and “Covid-19 pandemic” is still a lacuna in the literature. Of course, a considerable number of studies found to have used SEM, but they are all different with respect to data, variables, model, and other characteristics.

This research study proposes a reflective model. In a reflective measurement model the construct is the cause of the indicators (Ravand, Baghaei, 2019). This means Covid-19 mitigation can describe the efficacy of the practices related to “healthcare capacity”, “public immunity”. Figure 1 is the pictorial representation for studying model.

Figure 1: Study model

A screenshot of a computer screen with University of Oregon in the background

Description automatically generated

(Source: Created using *Inkscape* in Windows; Circles shown in the above figure represents study constructs. These constructs are treated as latent variables for data analysis. Each construct has a respective set of manifest variables for fitting data.)

The model presented in Figure 1 is the blueprint for this study. Circles in the figure show the latent variables and each of these latent variables are being explained by a few manifest/indicator variables. Table 1 has the list of manifest variables. The proposed model needs to be tested by the data and the final figure for this model comprising of estimates and other measures will be presented in the subsequent section called “data analysis”.

* 1. **Data sets**

There is abundant Covid-19 data available online. Collecting primary data through individual efforts may not be authentic. Pandemics or disease prevalence data needs to be collected or published by official protocols and with a national level vigilance. However, both primary and secondary data were used for this study. A thorough literature survey was conducted on 3rd August 2023, and data mining had been performed using Text Mining methodology. Table # shows the database information for literature survey.

Table #: Data sources for literature survey

|  |  |  |
| --- | --- | --- |
| Search statement | Source | Number of documents |
| Healthcare Facilities AND Immunization AND Covid-19 Mitigation | Scopus | 5 |
| Healthcare Facilities AND Covid-19 Mitigation | Web of Science | 68 |
| Immunization AND Covid-19 Mitigation | Web of Science | 42 |
| Total |  | 115 |

The World Health Organization (WHO) monitors much of the immunization activity. The second immunization pulse poll in the context of Covid-19 was conducted in June 2020. The poll was developed by WHO, UNICEF & Gavi, in collaboration with the Sabin Vaccine Institute’s Boost Community and the International Vaccine Access Center (IVAC) at Johns Hopkins and the Global Immunization Division/United States Centers for Disease Control and Prevention (CDCP). Data available on WHO portal was obtained for 260 respondents from 82 countries (WHO, 2020).

WHO lists 87 vaccines as a part of WHO vaccine-preventable diseases monitoring system (WHO, 2020). However, the number of vaccines approved for vaccination varies based on geography and disease prevalence of given country. For instance, Center for Disease Control and Prevention (CDCP) in USA approved 62 types of vaccines under 25 diseases. One of the WHO documents, with a title “Global and regional immunization profile”, lists 15 basic vaccines and mentions that the approvals are strictly country specific (WHO & WHO, 2023).

Government of India (GoI) approved 8 basic vaccines as through Expanded Program for Immunization (EPI), launched in 1978, to cover recommended vaccines for all Indian children (MoHFW, 2014 & MoHFW, 2016). Later GoI renamed the program as the Universal Immunization Program (UIP) in 1985, at which time it extended eight basic vaccines to all infants, pregnant women, and other adults (Irigoyen, 2017). The data set, related to vaccinations in India, was collected from WHO portal, with a title “WHO Vaccine-preventable diseases”. The data set has information related to a total 25 vaccines. Data related to vaccines that are listed in GoI’s UIP program were retained for analysis. The final data set is a 35 X 2 order data matrix consisting of state wise details of vaccination. Data sets used for this study especially related to “healthcare capacity” and “Covid-19 pandemic” were obtained from Ministry of Health and Family Welfare (MoHFW) portal (MoHFW., 2018 & MoHFW., 2020). This data set has 14 variables in total among which 10 variables are related to healthcare capacity and the rest i.e., 4 variables are related to Covid-19 pandemic. Table 1 shows the details of these variables.

Table 1: Variables related to healthcare capacity and Covid-19 pandemic.

|  |  |
| --- | --- |
| Construct/Latent variable | Manifest variable |
| Healthcare capacity | Number of Primary Health Centers |
| Number of Community Health Centers |
| Number of Sub-district Hospitals |
| Number of District Hospitals |
| Total Public Health Facilities |
| Number of Public Beds |
| Number of Rural Hospitals |
| Number of Rural Beds |
| Number of Urban Hospitals |
| Number of Urban Beds |
| COVID-19 Pandemic | Active Cases |
| Cured/Discharged/Migrated |
| Deaths |
| Total Confirmed cases |
| Immunization | Population obtained total 8 basic vaccines |

Table 1 shows the details of the latent variables along with their respective manifest variables. All manifest variables are numerical and continuous data variables. These variables were used as input variables for fitting study model, shown in Figure 1, using structural equation modeling.

* + 1. **Statistical Technique & Tools**

Structural equation modeling (SEM) is a set of statistical methods that fits data to a given model (Kaplan, 2009). SEM possesses a few techniques like Confirmatory Factor Analysis (CFA), path analysis (Kline, 2011). CFA used in structural equation modeling is significantly different from Exploratory Factor Analysis (EFA). Nevertheless, SEM like analyses were done even in EFA where structured diagrams are used to portray factors together with respective explanatory variables. For instance, “psych” package in R community supports SEM like procedures on EFA related methods (Revelle, 2019). “Psych” package doesn’t make SEM explicitly using EFA but uses factor analysis outputs to perform and obtain SEM like path diagrams (Revelle, 2018). This package is widely used by the research community, especially engaging in psychology with the objective of testing and modeling data using SEM. Structural equation modeling is a phrase made popular by researchers in social sciences (Tarka, 2018 & Guo, et al., 2009). However, SEM is referred to Latent Variable Analysis (LVA) in open-source programming communities like R (Michael, n.d.). Models are often invoked by a measurement model that defines latent variables using one or more observed variables, and a structural model that imputes relationships between latent variables.

In this article, SEM was performed using a package called “lavaan*”*. The package “lavaan*”* is widely used for structural equation modeling in R community (Rosseel Y., 2012). All the three constructs were tested by their respective manifest variables, shown in Table 1, using a very simple tri-component model. The model is said to be simple because there are no endogenous variables in the model. This research article tries to test cause-and-effect relationships between “healthcare capacity”, “immunization”, and their impact on “COVID-19 pandemic”. Table 2 shows model assumptions.

Table 2: Model assumptions and hypotheses

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Relationship | Estimates in the model | Constructs | Effect | Hypothesis |
| Direct | c | Healthcare capacity vs. COVID-19 pandemic | Cause-and-effect | H1 |
| Indirect | a | Immunization vs. healthcare capacity | Mediation | H2 |
| Indirect | b | COIVD-19 pandemic vs. Immunization | Mediation | H3 |

(Notes: c, a, b are estimates which need to be ascertained after fitting data to study model. See Figure 1 for these estimates and respective hypotheses.)

Relationship, in Table 2, refers to whether the association between given variables is director or indirect. The study assumes three relationships for testing direct and indirect effects. The relationship between “Healthcare Capacity” and “COIVD-19 Pandemic” is a direct relationship and this relation tries to test H1 throughestimate “a”. The impact of “Healthcare Capacity” on “Immunization” and “Immunization” on “Covid-19 pandemic” are indirect relationships and they are tested through H2, H3 through estimates “b”, “c” respectively. Indirect relationships are assumed to be explained by mediation effect in the model. This means, the study assumes that the impact, what-so-ever, presents between “Healthcare Capacity” and “COVID-19 Pandemic” is being mediated by “Immunization”. These assumptions are evaluated by performing Structural Equation Modeling (SEM) using “lavaan” package of R language in the forthcoming section.

1. **Analysis and Discussion**

Data was properly coded and edited well before performing analysis. All the manifest variables were arranged in proper fashion inside a CSV file. This file was imported into R programming language and the resultant data set is a 36 X 16 order data matrix. This data matrix was later converted into a data frame for analysis. First reliability analysis was performed to estimate internal consistency and reliability of the data. There are 16 manifest variables, so all these variables are treated as items for reliability analysis.

* 1. **Reliability analysis**

Reliability analysis was performed using “*psych”* package of R programming language. Table 3 shows the summary statistics related to a particular measure of internal consistency known as Cronbach Alpha together with a few other related statistics.

Table 3: Summary table for reliability analysis (Cronbach alpha)

|  |  |
| --- | --- |
| Name | Alpha |
| total.raw\_alpha | 0.940567a |
| total.std.alpha | 0.940567b |
| total.G6.smc. | 0.987912c |
| total.average\_r | 0.513392d |
| total.S.N | 15.82561e |
| total.ase | 0.012785f |
| total.mean | 2.10E-17g |
| total.sd | 0.738805h |
| total.median\_r | 0.54366 i |

(Source: Obtained through data analysis performed by using psych package of R (Revelle, W., 2019). a Raw alpha is the actual value for Cronbach alpha calculated by using covariances of variables. b Standardized alpha based upon correlations. c Guttman's Lambda 6 reliability. d the average inter-item correlation. e A measure for linearity called Singnal-Noise ratio. f Alpha standard error (ase). g Mean value of each item. h Standard deviation of each item. i Median inter item r.)

The Cronbach alpha value is 0.945 which appears to be robust value for internal consistency. All those values associated with Cronbach alpha also seem to support the fact that there exists internal consistency in the data and evidence appears to be invincible (Cronbach, 1951). Standard alpha, in Table 3, is a measure of reliability for items that arise from dissimilar contexts and this measure is also used to test construct validity (Hajjar, et al., 2018). In this study, the data related to the three constructs are obtained from different sources. This measure tests the assumption that whether it is possibility to combine such data, arising from variegated sources, together for analysis. Such an assumption can be construed to be true if there is a very minimal difference between raw alpha and standard alpha. The difference between raw alpha and standard alpha is zero. This is a huge welcoming sign in the analysis. This supports the fact that the construct validity is robust in the study. Guttman Lambda (G6), which indicates “lumpiness” in the data, is greater than Alpha and it shows that there are certain valid dimensions in the data (Revelle, 2020). All remaining measures, in Table 3, found to support Cronbach Alpha which means that the data has robust internal consistency and is suitable for further analysis. Table 4 shows the details related to Alpha drop in reliability analysis.

Table 4: Alpha drop in reliability analysis

|  |  |  |
| --- | --- | --- |
| Item/Manifest Variable | alpha.drop.raw\_alphaa | alpha.drop.std.alphab |
| Received.all.8.basic.vaccinations | 0.955265777 | 0.955265777 |
| Active.Cases | 0.93748696 | 0.93748696 |
| Cured.Discharged.Migrated | 0.935250302 | 0.935250302 |
| Deaths | 0.938843107 | 0.938843107 |
| Total.Confirmed.cases | 0.936221196 | 0.936221196 |
| NumPrimaryHealthCenters\_HMIS | 0.931883134 | 0.931883134 |
| NumCommunityHealthCenters\_HMIS | 0.933463931 | 0.933463931 |
| NumSubDistrictHospitals\_HMIS | 0.938419432 | 0.938419432 |
| NumDistrictHospitals\_HMIS | 0.936185993 | 0.936185993 |
| TotalPublicHealthFacilities\_HMIS | 0.931287141 | 0.931287141 |
| NumPublicBeds\_HMIS | 0.930954383 | 0.930954383 |
| NumRuralHospitals\_NHP18 | 0.941036005 | 0.941036005 |
| NumRuralBeds\_NHP18 | 0.93384753 | 0.93384753 |
| NumUrbanHospitals\_NHP18 | 0.931962811 | 0.931962811 |
| NumUrbanBeds\_NHP18 | 0.93272447 | 0.93272447 |

(Source: Obtained from data analysis performed by using “psych” package of R (Revelle, 2019). a Raw alpha value for Cronbach alpha. b Standard alpha value for Cronbach alpha.)

Alpha drop is construed to be one of the valid procedures in the reliability analysis while assessing relative importance of study variables. Table 4 has three columns; the first column shows the list of manifest variables and column two and three has values for raw alpha and standard alpha respectively. The raw and standard alpha values seem to be high (0.95) for “Immunization”. These values dropped to 0.93 for the rest of the variables in the data. The decrease whatsoever noticed does not seem to be significant. Moreover, the value stood steady for the rest of the manifest variables. This consistency in the alpha values shows that the reliability is not only acceptable but also robust in the data.

* 1. **Structural Equation Modeling (SEM)**

There are many types of analyses used in SEM. As it was mentioned earlier, the type of SEM done in this research study is known as reflective measurement model. All the latent variables defined in the model are exogenous in nature. All the manifest variables were used to test their respective latent variable which stands as research construct in the study. There are three research constructs in this study i.e., “healthcare capacity”, “immunization”, and “COVID-19 pandemic” and all these constructs are treated as latent variables. Table 5 has the output from the SEM performed by using R package called “lavaan”. The package “lavaan” has few steps to be followed by the analyst to test the proposed model. The very first step is to define an object called “model” using conventions of R programming. The “model” object is composed of all the relationships that are assumed or proposed by the study. Relationships in the model are defined by a few special characters shown in column number three (op) in Table 5. All relationships are equations with variables either side i.e., Left-Hand Side (LHS) and Right-Hand Side (RHS) of the equation. The symbol “=~” denotes the relationship between a latent variable and corresponding manifest variable. The symbol “~” defines regression equation. The symbol “~~” denotes covariance between variables in the equation and “:=” denotes the effect. Table 5 shows the summary statistics for SEM analysis.

Table 5: Summary statistics for SEM analysis

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| S. No. | lhsa | opb | rhsc | labeld | este | sef | zg | pvalueh |
| 1 | Pandemic | =~ | Active.Cases | 1 | 0 | NA | NA |
| 2 | Pandemic | =~ | Cured.Discharged.Migrated | 1.027641 | 0.051633 | 19.90268 | 0 |
| 3 | Pandemic | =~ | Deaths |  | 0.98639 | 0.064879 | 15.20352 | 0 |
| 4 | healthcap | =~ | NumPrimaryHealthCenters\_HMIS | 1 | 0 | NA | NA |
| 5 | healthcap | =~ | NumCommunityHealthCenters\_HMIS | 0.956775 | 0.102102 | 9.370737 | 0 |
| 6 | healthcap | =~ | NumSubDistrictHospitals\_HMIS | 0.753822 | 0.129703 | 5.811912 | 6.18E-09 |
| 7 | healthcap | =~ | NumDistrictHospitals\_HMIS | 0.82226 | 0.121791 | 6.751423 | 1.46E-11 |
| 8 | healthcap | =~ | NumPublicBeds\_HMIS | 1.03302 | 0.08759 | 11.79379 | 0 |
| 9 | healthcap | =~ | NumRuralHospitals\_NHP18 | 0.718934 | 0.133308 | 5.393033 | 6.93E-08 |
| 10 | healthcap | =~ | NumRuralBeds\_NHP18 | 0.982247 | 0.097566 | 10.06751 | 0 |
| 11 | healthcap | =~ | NumUrbanHospitals\_NHP18 | 0.934205 | 0.105875 | 8.823644 | 0 |
| 12 | healthcap | =~ | NumUrbanBeds\_NHP18 | 0.94184 | 0.104624 | 9.002166 | 0 |
| 13 | pandemic | =~ | Healthcap | c | 0.57146 | 0.127549 | 4.480311 | 7.45E-06 |
| 14 | Received.all.8.basic.vaccinations | ~ | Healthcap | a | 0.047476 | 0.214079 | 0.221771 | 0.824492 |
| 15 | pandemic | ~ | Received.all.8.basic.vaccinations | b | -0.16238 | 0.182343 | -0.89051 | 0.373192 |
| 16 | Active.Cases | ~~ | Active.Cases | 0.072584 | 0.021475 | 3.379915 | 0.000725 |
| 17 | Cured.Discharged.Migrated | ~~ | Cured.Discharged.Migrated | 0.021851 | 0.016453 | 1.328072 | 0.184154 |
| 18 | Deaths | ~~ | Deaths |  | 0.097056 | 0.025231 | 3.846659 | 0.00012 |
| 19 | NumPrimaryHealthCenters\_HMIS | ~~ | NumPrimaryHealthCenters\_HMIS | 0.156332 | 0.039924 | 3.915712 | 9.01E-05 |
| 20 | NumCommunityHealthCenters\_HMIS | ~~ | NumCommunityHealthCenters\_HMIS | 0.22581 | 0.053476 | 4.222631 | 2.41E-05 |
| 21 | NumSubDistrictHospitals\_HMIS | ~~ | NumSubDistrictHospitals\_HMIS | 0.510993 | 0.111039 | 4.601936 | 4.19E-06 |
| 22 | NumDistrictHospitals\_HMIS | ~~ | NumDistrictHospitals\_HMIS | 0.422389 | 0.093049 | 4.539449 | 5.64E-06 |
| 23 | NumPublicBeds\_HMIS | ~~ | NumPublicBeds\_HMIS | 0.101189 | 0.029937 | 3.379994 | 0.000725 |
| 24 | NumRuralHospitals\_NHP18 | ~~ | NumRuralHospitals\_NHP18 | 0.5532 | 0.119621 | 4.624614 | 3.75E-06 |
| 25 | NumRuralBeds\_NHP18 | ~~ | NumRuralBeds\_NHP18 | 0.18524 | 0.045493 | 4.071812 | 4.66E-05 |
| 26 | NumUrbanHospitals\_NHP18 | ~~ | NumUrbanHospitals\_NHP18 | 0.260869 | 0.060461 | 4.31465 | 1.60E-05 |
| 27 | NumUrbanBeds\_NHP18 | ~~ | NumUrbanBeds\_NHP18 | 0.249104 | 0.058111 | 4.286703 | 1.81E-05 |
| 28 | Received.all.8.basic.vaccinations | ~~ | Received.all.8.basic.vaccinations | 0.984563 | 0.211106 | 4.663841 | 3.10E-06 |
| 29 | pandemic | ~~ | pandemic |  | 0.887196 | 0.202244 | 4.386766 | 1.15E-05 |
| 30 | healthcap | ~~ | healthcap |  | 0.530494 | 0.13485 | 3.933969 | 8.36E-05 |
| 31 | Ab | := | a\*b | ab | -0.00771 | 0.040684 | -0.18949 | 0.849711 |
| 32 | Total | := | c+(a\*b) | total | 0.563751 | 0.126581 | 4.45368 | 8.44E-06 |

(Source: Obtained through data analysis performed by using *lavaan* package of R (Rosseel, Y., 2012). a LHS (Left Hand Side) of the relationship in SEM model definition. b Operator used in SEM model definition. c RHS (Right Hand Side) of the relationship in SEM model definition. d Labels assigned for equations related to cause-and-effect relationships. e Estimates for relationship, or equation, in the model specification. f Standard Error (se) for relationship in the model specification. g Standard normal value (z). h P Value.)

All the constructs viz., “Covid-19 Pandemic”, “Healthcare Capacity” and “Immunization” were identified significantly by their respective manifest variables. All the P Values are close to zero. Moreover, estimates for relationships at primary level, i.e., between constructs and their respective manifest variables appeared to be close to one. This shows that there is a required amount of fitness in the model proposed by this research study.

Hypothesis 1 (H1) addresses the impact of “healthcare capacity” on “Covid -19”. This hypothesis assumes a direct relationship between “healthcare capacity” and “Covid-19 pandemic”. The coefficient “c”, in Table 5, explains this relationship. The value for “c” is 0.57146 and P Value for the same is close to zero (7.45E-06). So, H1 is accepted.So, the impact of “healthcare capacity” on “Covid-19 pandemic” is statistically significant. In other words, the cases, deaths, and active cases can be explained by the number of beds and hospitals at both rural and urban areas.

The other important proposition of the study is mediation effect explained by “Immunization”. This hypothesis gives rise to two other relationships, refer to Table 2, through hypotheses H2 and H3. The hypotheses explain indirect effects in the model. The coefficients in Table 5 i.e., “a” and “b” measure these indirect effects. Both these estimates do not appear to be statistically significant (a = 0.047476, P Value = 0.824492; b = -0.16238, P Value = 0.373192). Both these hypotheses can be rejected because they are not statistically significant in the study. However, the total effect i.e., c + (a\*b) explained through all the effects found to be statistically significant [c + (a\*b) = 0.563751; P Value = 8.44E-06]. “Immunization” may not be a mediating variable but may be a spurious variable. Hence, the study assumes that though “Immunization” is not significant while explaining mediation but its presence do make the relationships in the whole model significant. Table 5 shows the details of fit measures obtained from SEM analysis for the study model.

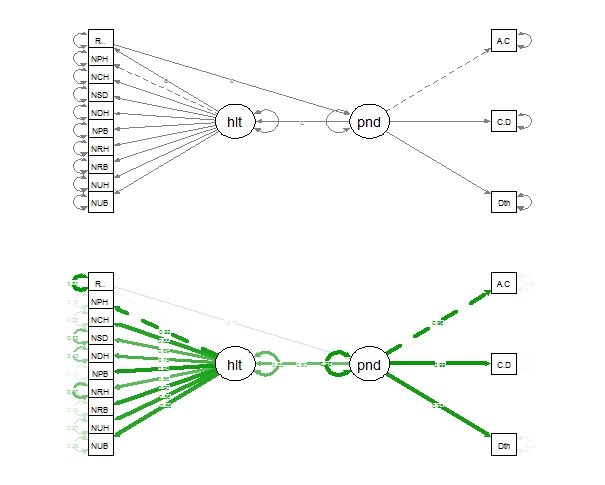
Table 6: Fit measures for study model.

|  |  |
| --- | --- |
| Fit Measure | Value |
| Npar | 28 |
| Fmin | 4.107965 |
| Chisq | 369.7168 |
| Df | 63 |
| pvalue | 0 |
| baseline.chisq | 976.6778 |
| baseline.df | 78 |
| baseline.pvalue | 0 |
| Cfi | 0.958702 |
| Tli | 0.877441 |
| Logl | -520.025 |
| unrestricted.logl | -335.167 |
| Aic | 1096.05 |
| Bic | 1146.637 |
| ntotal | 45 |
| bic2 | 1058.869 |
| rmsea | 0.128922 |
| rmsea.ci.lower | 0.106917 |
| rmsea.ci.upper | 0.26176 |
| rmsea.pvalue | 0 |
| Srmr | 0.015784 |

(Source: Obtained through data analysis performed by using lavaan package of R (Rosseel, Y., 2012).

All the fit measures for the model appear to be fair and explain the best fit for study data. Measures like CFI, TLI are close to one (0.958, 0.877) and measures which represent error such as RMSEA, SRMR found to be minimum (0.128, 0.015). This shows that the model proposed by the study is the best of its kind while fitting data. Figure 2, adds the visualization to the above interpretation.

Figure 2: Study model obtained through SEM analysis.



(Source: Obtained from data analysis. Figure represents the model proposed by the study and tested through the technique called Structural Equation Modeling (SEM). This figure was obtained by using lavaan package in R programming language.)

Letters in Figure 1 such as “*c”, “a”* and “*b”* are direct and indirect estimates in the model. The direct estimate “c” is 0.57146, with a P Value being 7.45E-06, is statistically significant. This means there is evidence in support of Hypothesis H1. Letters “*a”* and “*b”* represent estimates for indirect effect (a\*b). The estimate for indirect effect is 0.00771 with a P Value being 0.849711 and is not statistically significant, which shows that there is no evidence in support of Hypothesis H2. The total effect, (c + a\*b), is 0.563751 with a P Value being 8.44E-06 and it is statistically significant. So, there is evidence in support of Hypothesis H3.

1. **Conclusion**

The primary objective of this study is to assess the impact of “healthcare capacity” on “Covid -19 pandemic” assuming mediation effect from “public immunity”. Therefore, this study assumes three hypotheses to evaluate such assumptions. The first hypothesis (H1) is related to causal relationship between healthcare capacity and Covid-19 pandemic. The second hypothesis (H2) is related to mediation effect explained by immunization. Data was collected from certain secondary but official and internationally reputed sources. Data was verified for reliability, also known as internal consistency, and found fit for the analysis (α, γ > 0.9). Structural Equation Modeling (SEM) was performed to evaluate study hypotheses. Analysis shows evidence in support of the first hypothesis (H1). This means, the relationship between “healthcare capacity” and “Covid -19 pandemic” is a cause-and-effect relationship and it is statistically significant. The study answers RQ1 as “Healthcare capacity”, which is defined by number of hospitals and beds at both rural and urban areas, do impact “Covid-19 mitigation”. However, there is no evidence in support of the second and third hypotheses (H2 and H3). So, the mediation effect assumed by “public immunity” over the main relationship i.e., the relationship between “healthcare capacity” and “Covid-19 pandemic” is not statistically significant. The answer to RQ2 is that “Immunization” may not impact “Covid-19 pandemic”. Albeit of this, certain spurious relationships between study constructs do exist. This means, though there is no palpable evidence in support mediation of “immunization” but it was found to have certain spurious impact over the main relationship between “healthcare capacity” and “COVID-19 pandemic”. This study finally concludes that “healthcare capacity” is important when taking any decisions of “COVID-19 pandemic”. The decision makers may not be able consider or mix with decisions of “public immunity” together with “healthcare capacity”.

1. **Research Implications and Future Directions**

This study may be useful for healthcare administrators, policy makers and other clinical and non-clinical staff working in the healthcare domain. Today, Covid-19 turned out to be a global pandemic for perpetuity. Covid-19 cases together with deaths rose exponentially irrespective of geographical, cultural, and economic disparities across the globe. Healthcare capacity and public immunity appeared as two potential alternatives to address the pandemic. The question that whether healthcare capacity truly impact Covid-19 pandemic is still valid till today. This paper addresses this question with the help of data analysis supported by research methods. This article suggests “Healthcare Capacity” as a potential solution compared to “Immunization”. Decision makers need to consider the “Healthcare facilities” as primary driver for mitigating pandemics. The effect of “Immunization” over “Covid-19 pandemic” is still a question, and which needs to be answered in future research endeavors. This research study has few limitations. Mainly, this study may not be important for clinical decisions but may be useful to policy makers or innovators. The analysis was done using Indian data, so the results and findings are applicable to Indian geography. It is highly recommended to extend this study by changing data specifically related to different geographic locations on the globe.

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