PROJECT REPORT

"Data Engineering with AI & Analytics: COVID-19 Data "

REPORT SUBMITTED FOR THE PARTIAL FULFILMENT OF THE REQUIREMENT FOR

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In

COMPUTER SCIENCE & ENGINEERING

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CERTIFCATE

This is to certify that the project entitled **“Data Engineering with AI & Analytics: Covid-19 Data ”** submitted by **Vivek Maurya , Suchit Sharma , Shivam Pal, Anoop Kumar Gupta** in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology(CSE)** of **Dr.A.P.J. Abdul Kalam Technical University**, is a record of the student’s own work carried out under my supervision and guidance. The project report embodies results of the original work and studies carried out by the students, and the contents do not form the basis for the award of any other degree or diploma to the candidate or to anybody else.

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DECLARATION

We hereby declare that the project entitled **"Data Engineering with AI & Analytics: Covid-19 Data "** submitted by us in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology (CSE)** of **Dr. A.P.J. Abdul Kalam Technical University** is a record of our own work carried out under the supervision and guidance of **Mr. Dileep Kumar Gupta (Assistant Professor, CSE Dept.)**.

To the best of our knowledge and belief, this project has not been submitted to **Dr. A.P.J. Abdul Kalam Technical University** or any other University or Institute for the award of any degree or diploma.

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BONAFIDE CERTIFICATE

This is to certify that the project report entitled **"Data Engineering with AI & Analytics: Covid-19 Data "** submitted by **Vivek Maurya , Suchit Sharma , Shivam Pal, Anoop Kumar Gupta** to **Goel Institute of Technology, Lucknow** in partial fulfillment of the requirement for the award of the degree of **B.Tech in CSE** is a record of the project undertaken by them under my supervision.
The report fulfills the requirements as per the regulations of this Institute and, in my opinion, meets the necessary standards for submission. The contents of this report have not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this Institute or any other Institute or University.

SUPERVISOR

Date:

Internal Examiner (s) **External Examiner (s)**

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Abstract

The disasters caused by epidemic outbreaks is different from other disasters due to two specific features: their long-term disruption and their increasing propagation. Not controlling such disasters brings about severe disruptions in the supply chains and communities and, thereby, irreparable losses will come into play.

Coronavirus disease 2019 (COVID-19) is one of these disasters that has caused severe disruptions across the world and in many supply chains, particularly in the healthcare supply chain. Therefore, this paper, for the first time, develops a practical decision support system based on physicians' knowledge and fuzzy inference system (FIS) in order to help with the demand management in the healthcare supply chain, to reduce stress in the community, to break down the COVID-19 propagation chain, and, generally, to mitigate the epidemic outbreaks for healthcare supply chain disruptions.

This approach first divides community residents into four groups based on the risk level of their immune system (namely, very sensitive, sensitive, slightly sensitive, and normal) and by two indicators of age and pre-existing diseases (such as diabetes, heart problems, or high blood pressure). Then, these individuals are classified and are required to observe the regulations of their class. Finally, the efficiency of the proposed approach was measured in the real world using the information from four users and the results showed the effectiveness and accuracy of the approach.

One of the problems now confronting societies is the lack of equipment to successfully encounter this virus. This virus propagates rapidly, so any failure in dealing with its prevalence dramatically increases the number of infected people. If communities are

faced with a shortage of medical/healthcare equipment, an increase in the number of

infected people can initiate catastrophe. Healthcare equipment and services, such as coronavirus testing kits, masks, gloves, etc. are not available to all the people in the society.

Therefore, an effective way to make optimal use of the available healthcare equipment and to manage the demands in the healthcare supply chain is to identify and classify the individuals with and without COVID-19 and, accordingly, to propose instructions/regulations for each class. Generally, the main purpose of this study is to respond to the following research questions:

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INTRODUCTION

1.1 Overview of Project

The COVID-19 pandemic has been one of the most significant global health crises in recent history, prompting an unprecedented worldwide vaccination campaign. While vaccines played a critical role in reducing infection rates, preventing severe disease, and saving countless lives, the post-vaccination phase has introduced a new area of scientific inquiry. Observations suggest the emergence of various health conditions and diseases that may have coincided with or followed mass vaccination efforts. Understanding whether these occurrences are causally linked, correlated, or merely coincidental requires thorough investigation and robust data analysis.

This project focuses on analyzing data related to diseases and health conditions reported after COVID-19 vaccination. The primary objective is to identify patterns, trends, and potential correlations between vaccination and newly observed diseases or adverse health outcomes. By leveraging large datasets, including clinical records, health surveys, and publicly available vaccination-related data, the analysis aims to provide evidence-based insights into post-vaccination health impacts.

The project will employ advanced statistical analysis techniques, machine learning algorithms, and data visualization tools to interpret complex datasets. Key areas of focus include identifying disease clusters, assessing demographic and geographical patterns, and exploring predisposing factors that might contribute to post-vaccination health conditions. Furthermore, the analysis will consider variables such as age, vaccine type, comorbidities, and pre-existing health conditions to ensure a comprehensive understanding.

The outcomes of this project are expected to contribute significantly to public health strategies, healthcare policy-making, and vaccine safety monitoring. By identifying any potential risks or health trends associated with vaccination, healthcare professionals can enhance post-vaccination monitoring systems, improve patient care, and foster greater public confidence in vaccination campaigns.

In conclusion, this project serves as a crucial step towards bridging the knowledge gap in post-vaccination disease analysis, ensuring that the global community remains prepared to address emerging health challenges in the aftermath of the COVID-19 pandemic.

1.2 Identification of need

In this project, the performance of individual classifiers as well as the ensemble of classifiers that utilize different learning paradigms and voting schemes will be compared in terms of detection accuracy and false negative rates. At the end of this comparison, the algorithm that demonstrates better performance in terms of detection accuracy and low false negative rates will be highlighted.

The needs are-

There are numerous studies and reports analyzing diseases occurring after vaccination, but many of them lack reliable and accurate predictive algorithms to identify potential patterns and correlations. Therefore, we need an algorithm in the backend with high accuracy.

Very few existing systems leverage machine learning algorithms to analyze disease occurrence post-vaccination, leading to limited accuracy and reliability in predictions. Thus, there is a need for a system that utilizes advanced machine learning algorithms to ensure robust and accurate analysis.

LITERATURE REVIEW

To date, a large number of studies have been done on supply chain network design under disruptions in a variety of domains, such as supplier selection and order allocation (PrasannaVenkatesan and Goh, 2016), biofuel supply chain (Fattahi and Govindan, 2018), reverse supply chain (Hosseini-Motlagh et al., 2019), blood supply chain (Hamdan and Diabat, 2020), fashion supply chain (Zhao et al., 2020), etc. by means of mathematical programming tools. In this regard, some studies have even touched upon the impacts of epidemic outbreaks on supply chains (Ivanov, 2020, Choi, 2020). In the following, Section 2.1 examines the concept of disaster management. Section 2.2 discusses the studies undertaken in operations management related to diseases or epidemic outbreaks. At the end, Section 2.3 is dedicated to the introduction of FIS.

2.1. Disaster management

As suggested by Carter (1992), a disaster management cycle is an attempt to plan the strategies and measures that are at play from the beginning to the end of a disaster's lifespan. This framework has been repeatedly modified (Tomasini and Wassenhove, 2009) in such a way that it currently entails two phases (relief and development) and four activities (preparedness, rehabilitation, response, and mitigation) (Ahmadi et al., 2015). In addition, both of the mentioned phases have some activities as subcategories. For example, response and rehabilitation are two activities included in the relief phase, and the two other activities, preparedness and mitigation, are placed in the development phase (Goldschmidt and Kumar, 2016, Loree and Aros-Vera, 2018).

Activities and measures preplanned to guarantee the effectiveness of responses to the impact of risks and threats, such as pertinent hazards warnings or the temporary evacuation of occupants from homes and workplaces exposed to disasters, fall within the category of preparedness (Shahparvari et al., 2016). Indeed, these activities seek to minimize the negative effects of such disasters and to devise relevant strategies within the realm of socio-economic, physical, and environmental domains (Wang and Wang, 2019). In this regard, efforts to provide effective responses should encompass various factors, such as resources, urgent measures for life saving, environmental conservation, and the socio-economic and political status of the affected society (Altay and Green, 2006).

In the same way, activities grouped within the rehabilitation domain seek not only to rebuild damaged areas and properties but also to establish a new situation significantly better than the previous one. Rehabilitation actions are designed to avoid similar detrimental effects of future disasters by exercising resilience (Goldschmidt and Kumar, 2016).

Mitigation efforts seek to either prevent the initiation of a disaster or to decrease the damages that may come into play (Sheu, 2016, Hossain and Paul, 2018).

2.2. Epidemic outbreaks of disease

Epidemic outbreaks are specifically considered among supply chain disruptions. Further, they denote a particular variety of threat in the supply chain, which is recognized by the three following components: (1) the presence of long-term and unexpected scaling disruption, (2) disruption propagation in the supply chain and epidemic outbreak propagation in the population, and (3) disruptions in the infrastructure of logistics, demand, and supply. In contrast to most disruption threats and risks, epidemic outbreaks are minor at the outset, but they develop and spread over various geographic areas very quickly (He and Liu, 2015). The latest pertinent examples include MERS, SARS, Swine flu, Ebola, and the newest one, coronavirus. The COVID-19 outbreak started in Wuhan, China and quickly affected the Chinese economy; as a result, supplies in worldwide supply chains were considerably diminished. Accordingly, Araz et al. (2020) has asserted that the outbreak of this viral disease is one of the most critical disruptions to occur in recent decades and, thereby, it is ravaging a large portion of supply chains across the world.

To investigate epidemic outbreaks that struck before that of COVID-19, one will find limited information in connection with supply chain measures. For example, Johanis (2007) analyzed a pandemic response plan that was designed at Toronto’s Pearson International Airport after undergoing the harmful effects of SARS epidemic outbreak in 2002–2003. This virus terribly influenced the global airline industry; in fact, airlines in Taiwan suspended about 30% of international flights (Chou et al., 2004). However, the spread rate of the SARS virus and

China's role in the critical situation of SARS totally differed from that of the current COVID-19 virus;

accordingly, SARS had lower adverse effects on the SCs. Similarly, the spread of the Ebola virus badly affected worldwide logistics (BSI, 2014). In this regard, Büyüktahtakın et al., 2018, Calnan et al., 2018 shed some light on the valuable experiences obtained while Ebola virus was dominant. They called for the development of a decision-support framework through which epidemic outbreaks might be predicted and their effects on the supply chains could be facilitated. With such a framework, required measures and logistic policies could be adopted during and following the disaster. Ivanov (2020) studied the impact of epidemic outbreaks on supply chain networks. He specifically considered the propagation of the COVID-19 virus on global networks using characteristics of the uncertainty type. As for the methodology, Anylogic software was used to predict and simulate both short- and long-term impacts. Experiments show that closing and opening dates of facilities are the most impactful factors in the propagation. The results could help decision makers to mitigate the uncertainties and to curb or decelerate propagation.

Fuzzy inference system

As a nonlinear system, FIS is obtained from the integration of expert system technology and fuzzy logic (Lin et al., 2012). This system includes a set of fuzzy IF-THEN rules that are arranged based on experts' or decision-makers' knowledge. Such rules are used in this system for simulating the process of human reasoning. FIS has some advantages, such as the benefiting from human knowledge and changeable rules to indicate experts' judgment (Asklany et al., 2011, Tavana et al., 2019). In this vein, fuzzy logic modeling techniques fall within two groups, either the Mamdani (Mamdani and Assilian, 1993) or the Takagi-Sugeno-Kang (Sugeno, 1985). The fuzzy sets of antecedents and their consequences are the constituents of Mamdani models, but only the antecedents are placed in the Takagi-Sugeno-Kang model where the consequence here entails linear equations. The main purpose of fuzzy relational equation models is to create such fuzzy relation matrices based on data of the input–output process (Khajeh and Modarress, 2010). In this manner, Takagi-Sugeno-Kang FIS undergoes some problems, especially regarding the accomplishment of the multi-parameter synthetic evaluation and the weight assessment of inputs and fuzzy rules. The positive features of the Mamdani model – particularly, its legibility and understandability – are evident to laypersons. The Mamdani FIS is advantageous over other models in terms of output expression (Chai et al., 2009).

FIS is an applied tool in various areas, such as risk management (Ilbahar et al., 2018, Chung et al., 2019), supplier selection (Amindoust et al., 2012, Jain and Singh, 2020, Jain et al., 2020), manufacturing systems evaluation (Pourjavad and Mayorga, 2019), healthcare supply chain (Nazari et al., 2018), and so forth.

In this paper, a Mamdani FIS is used to classify the community residents so demand can be managed in a healthcare supply chain under the disaster arising from COVID-19. Further, the model strives to control epidemic outbreaks of this disease and to mitigate supply chains disruptions that pertain to healthcare supply chains.

However, the use of expert-based and management tools to control epidemic outbreaks and to mitigate supply chain disruptions has not received much attention. Accordingly, a decision support system based on FIS and physicians' knowledge is developed for this purpose in this study.

METHODS

The COVID-19 data from 30th January 2020 to 27th March 2022 for India was retrieved from several official websites such as www.mygov.in/COVID-19 and www.mohfw.gov.in, important resources, i.e., ourworldindata.org/coronavirus and COVID19.who.int and reputed Indian newspapers such as Hindustan Times and Times of India.

More than 50 research articles, reviews, mini-reviews, and reports have been cited that narrate the actual scenario on strategies and issues regarding COVID-19. This involves testing, approval, and temporal vaccination statistics, vaccination hesitation among population and gender, especially in women, and the social and economic impact of this pandemic. The collected data was analyzed and split into sections covering COVID-19 testing, vaccines and vaccination hesitation, and, economic impact

We summarized all the details of the COVID-19 pandemic surge and retraction in India for every sector as per changing timescale. A special focus has been given to the articles that offered quantitative evidence regarding the healthcare system response, clinical data of patients, and clinical manifestations related to COVID-19.

The data engineering process began with data acquisition, followed by data preprocessing and cleaning to ensure accuracy, consistency, and reliability. Duplicate entries, inconsistencies, and null values were addressed systematically. The data was then transformed into structured datasets suitable for downstream analysis.

The cleaned datasets were categorized into the following key sections:

- ❖ **COVID-19 Testing Trends:** Analyzed testing rates, testing methodologies, and the effectiveness of testing infrastructure across different phases of the pandemic.
- ❖ **Vaccines and Vaccination Hesitancy:** Explored vaccine rollout strategies, public acceptance, vaccination gaps across genders, and key demographic barriers.
- ❖ **Economic Impact of COVID-19:** Examined the pandemic's effects on economic growth, employment rates, sector-specific losses, and recovery measures.

To ensure clarity and insight-driven analysis, data was processed through data pipelines that involved tasks such as data normalization, feature engineering, and aggregation at various temporal and spatial levels. Visualization tools and statistical analysis techniques were applied to identify trends, patterns, and anomalies.

A significant emphasis was placed on quantitative evidence to validate findings, including:

- **Healthcare system response efficiency**
- **Clinical data analysis of patient outcomes**
- **Key clinical manifestations and treatment effectiveness**

Temporal analysis played a crucial role in summarizing the pandemic's progression and regression, capturing distinct phases such as the initial outbreak, peak surges, vaccination drives, and periods of decline. Each phase was analyzed in correlation with policy interventions, public behavior, and healthcare resource allocation.

The data engineering workflow ensured reproducibility and scalability, enabling future researchers and stakeholders to build on the existing datasets and findings. The integration of data visualization dashboards further facilitated intuitive understanding and real-time monitoring of COVID-19 trends.

Overall, this methodological approach provided a structured framework for analyzing large-scale COVID-19 datasets, bridging the gap between raw data collection, preprocessing, and actionable insights. This project serves as a robust foundation for future studies leveraging data engineering techniques to address global health crises.

DISEASES

Heart Disease and the Emergence of New Health Conditions Post-COVID-19 Vaccination

The COVID-19 pandemic led to the rapid development and deployment of vaccines to curb the spread of the virus and mitigate severe disease outcomes. While these vaccines have proven effective in reducing hospitalizations and deaths, rare adverse effects and new health conditions have been observed in some individuals. Among these, heart disease and other emerging diseases post-vaccination have garnered significant attention. This report explores the connection between COVID-19 vaccines, heart disease, and other new health conditions based on available data.

Overview of COVID-19 Vaccines

COVID-19 vaccines, such as those developed by Pfizer-BioNTech, Moderna, AstraZeneca, and Johnson & Johnson, employ various technologies, including mRNA and viral vector platforms. These vaccines stimulate the immune system to recognize and combat SARS-CoV-2, significantly reducing the risk of severe illness and death.

Despite their effectiveness, no medical intervention is without risk. Regulatory agencies have identified rare adverse events, prompting continuous monitoring and research. Vaccines' benefits far outweigh the risks, but understanding these rare outcomes is crucial for public health.

Heart Disease and COVID-19 Vaccines

1. **Myocarditis and Pericarditis**

Myocarditis (inflammation of the heart muscle) and pericarditis (inflammation of the lining around the heart) are among the most documented heart-related side effects of COVID-19 vaccines. These conditions have been reported predominantly in younger males following the second dose of mRNA vaccines (e.g., Pfizer-BioNTech and Moderna).

Incidence Rates: According to studies, myocarditis occurs at a rate of approximately 10 to 20 cases per million doses in young males.

Symptoms: Chest pain, shortness of breath, and palpitations usually manifest within a few days post-vaccination.

Prognosis: Most cases are mild and resolve with medical treatment, though long-term monitoring is recommended.

2. Thrombosis with Thrombocytopenia Syndrome (TTS)

TTS is a rare condition involving blood clots and low platelet levels. It has been associated with viral vector vaccines such as AstraZeneca and Johnson & Johnson.

Risk Factors: Primarily observed in women under 50.

Management: Early detection and appropriate treatment have improved outcomes.

New or Aggravated Diseases Post-Vaccination

1. **Exacerbation of Pre-existing Conditions**

In some cases, vaccination may unmask or exacerbate undiagnosed or pre-existing conditions. For instance:

Hypertension and Arrhythmias: Individuals with undiagnosed hypertension may experience transient spikes in blood pressure.

Autoimmune Responses: Rarely, vaccines can trigger autoimmune conditions in predisposed individuals.

2. **Immune-Mediated Conditions**

Guillain-Barré Syndrome (GBS): A rare neurological disorder causing muscle weakness and paralysis, GBS has been reported post-vaccination, particularly with viral vector vaccines.

Multisystem Inflammatory Syndrome (MIS): Though more common post-COVID-19 infection, rare cases of MIS have been noted post-vaccination.

3. **Long COVID and Post-Vaccine Syndrome**

Some individuals report persistent symptoms akin to long COVID following vaccination. These include fatigue, brain fog, and joint pain. While mechanisms remain unclear, ongoing research aims to delineate these conditions.

Safety Monitoring Systems:

Systems like VAERS (U.S.), Yellow Card Scheme (UK), and EudraVigilance (EU) track and analyze adverse events post-vaccination.

Data shows that while severe adverse events are rare, transparency and reporting are vital for public trust.

Comparative Risks:

The risk of heart complications from COVID-19 infection far exceeds the risks posed by vaccines. For example, myocarditis incidence is significantly higher in COVID-19 patients compared to vaccinated individuals.

Demographic Patterns:

Young males are at higher risk for myocarditis, whereas TTS is more prevalent in younger females receiving viral vector vaccines.

Recommendations and Future Directions

Public Health Communication:

Emphasize the comparative safety of vaccines versus COVID-19 complications.

Provide clear guidance on recognizing and managing adverse events.

Individualized Risk Assessment:

Encourage individuals with pre-existing conditions to consult healthcare providers before vaccination.

Develop risk stratification tools to identify susceptible populations.

Ongoing Research:

Conduct large-scale epidemiological studies to understand long-term effects.

Investigate mechanisms underlying rare adverse events to improve vaccine design.

Enhanced Reporting Systems:

Strengthen global collaboration for real-time data sharing.

Ensure transparency to foster public trust in vaccination programs.

COVID-19 vaccines remain a cornerstone in controlling the pandemic. While rare adverse events and new health conditions post-vaccination warrant attention, their overall safety profile is robust. The risk of severe outcomes from COVID-19 infection far outweighs vaccine-associated risks. Continued surveillance, research, and transparent communication are essential to addressing public concerns and enhancing vaccine confidence. By balancing the benefits and risks, vaccination programs can protect public health while addressing individual needs.

Neurological Complications

Introduction and Definition: COVID-19 is not just a respiratory illness; it also impacts the nervous system. Neurological complications associated with COVID-19 include stroke, encephalitis, Guillain-Barré syndrome, and peripheral neuropathy. The National Institute of Neurological Disorders and Stroke (NINDS) highlights the importance of understanding these complications to improve patient care.

Symptoms and Manifestations: Neurological symptoms vary widely and may include severe headaches, confusion, seizures, loss of smell and taste, and dizziness. Severe cases may present with stroke, brain inflammation, and nerve damage. Long-term complications include chronic fatigue, memory problems, and cognitive impairment.

Causes and Risk Factors: Neurological issues may arise from direct viral invasion of neural tissues, immune system overreaction, or secondary effects such as reduced oxygen supply to the brain. Risk factors include older age, underlying neurological disorders, and severe COVID-19 infection.

Impact on Patients and Healthcare Systems: Neurological complications significantly burden healthcare systems due to the need for specialized care and long-term rehabilitation.

Patients often require ongoing therapy, including physical therapy, speech therapy, and cognitive rehabilitation.

Current Research and Treatment Approaches: Treatment focuses on managing individual symptoms. Stroke patients may require anticoagulants, while inflammation is addressed with corticosteroids or immunotherapies. Research continues to explore the virus's effects on the nervous system.

Preventive Measures: Vaccination and prompt medical intervention for neurological symptoms in COVID-19 patients are crucial preventive strategies.

Fungal Infections

Introduction and Definition: Fungal infections, notably mucormycosis (black fungus), have surged among COVID-19 patients, especially in regions with high corticosteroid use and uncontrolled diabetes. These infections are aggressive and require immediate medical attention.

Symptoms and Manifestations: Common symptoms include facial swelling, nasal congestion, black lesions in the nasal cavity, blurred vision, and fever. In severe cases, the infection can spread to the brain, lungs, and gastrointestinal tract.

Causes and Risk Factors: Risk factors include prolonged steroid use, diabetes, weakened immunity, and prolonged ICU stays. Poor hospital hygiene and unsterilized medical equipment have also been implicated.

Impact on Patients and Healthcare Systems: Fungal infections are challenging to treat and require antifungal medications or surgical debridement of infected tissues. This places a significant financial and resource burden on healthcare systems.

Current Research and Treatment Approaches: Treatment includes antifungal medications like amphotericin B and surgical removal of infected tissues. Research focuses on better diagnostic tools and antifungal therapies.

Preventive Measures: Proper diabetes management, judicious steroid use, and maintaining hygiene in hospital settings are essential for preventing fungal infections.

Impact on Chronic Disease Management

Introduction and Definition: The COVID-19 pandemic disrupted routine healthcare services globally, impacting the diagnosis, treatment, and management of chronic diseases such as diabetes, cardiovascular diseases, and cancer.

Symptoms and Manifestations: Delays in medical consultations, missed follow-up appointments, and interruptions in medication supplies have led to disease progression, complications, and increased mortality rates among chronic disease patients.

Causes and Risk Factors: Lockdowns, fear of virus exposure, and healthcare resource reallocation are major contributors to these disruptions.

Impact on Patients and Healthcare Systems: Healthcare systems face long-term challenges, including increased hospital admissions and the need for intensive interventions for advanced chronic diseases.

Current Research and Treatment Approaches: Telemedicine and virtual consultations have emerged as key solutions for addressing gaps in chronic disease care. Research focuses on optimizing digital healthcare delivery.

Preventive Measures: Strengthening healthcare infrastructure, ensuring medication supply chains, and promoting remote healthcare services are vital for improving chronic disease management outcomes.

PROBLEM STATEMENT & PROPOSED APPROACH

Many societies have proposed solutions to address disasters and have taken measures tailored to their preparedness, response, rehabilitation, and mitigation activities regarding disaster control. For example, many countries minimize human, economic, and environmental losses in the face of disasters such as floods, earthquakes, storms, etc. by means of proper disaster management (Rezaei-Malek et al., 2016, Acar and Kaya, 2019). Effective management of these kinds of disasters benefits from past similar experiences and historical data (Yan et al., 2017).

Such disasters are not of epidemic scale and they affect only parts of a country; further, they last for a short duration. The localized nature of such disasters presents the possibility that non-affected countries can help the disaster-stricken society. However, the ability to assist takes a different shape when a novel, long-running, and rapidly growing disaster such as COVID-19 emerges. Such a disastrous situation confuses decision-makers and governments and disrupts almost all community activities and supply chains. Since COVID-19 is a new and unknown virus, it has many unknown aspects and, thereby, the identification of and access to some of these aspects is time-consuming and costly; more importantly, it endangers the lives of many humans.

Many communities face a shortage of medical and human resources (treatment staff) under such conditions due to the high rate of disease outbreaks. This heightened demand for services leads to disruptions among many supply chains, but especially with the healthcare supply chain. Therefore, the prioritization of community members for the provision of better services and solutions to manage the demand in the healthcare supply chain can improve government performance and reduce disruptions in this chain.

However, it should be noted that it is not possible to give all people in one community the same prescription. In other words, each group of the society has specific characteristics that differentiate their needs from those of another group. Thus, older residents and those with pre-existing diseases (such as diabetes, heart problems, or high blood pressure) are more vulnerable according to World Health Organization (WHO) reports. Accordingly, the community members are subdivided into four groups based on their level of vulnerability to COVID-19:

- Very sensitive group: People over 60 years of age who suffers at least one of the diseases of diabetes, heart problems, or high blood pressure.
- Sensitive group: People below 60 years of age with at least one of the diseases of diabetes, heart problems, or high blood pressure.

When it comes to the classification of the members of the aforementioned groups, various approaches based on FIS accomplish that. In other words, the FIS is used to classify individuals of the society, but the fuzzy inference rules will be different for each group of people in the society. In Fig. 2, the structure of the decision support system for demand management in the healthcare supply chain has been depicted. This proposed decision support system, indeed, acts as a connecting bridge between service recipients and service providers in the healthcare supply chain. In this way, this decision support system provides the grounds for demand management in the healthcare supply chain by classifying the service recipients. The proposed approach is also described in the following steps:

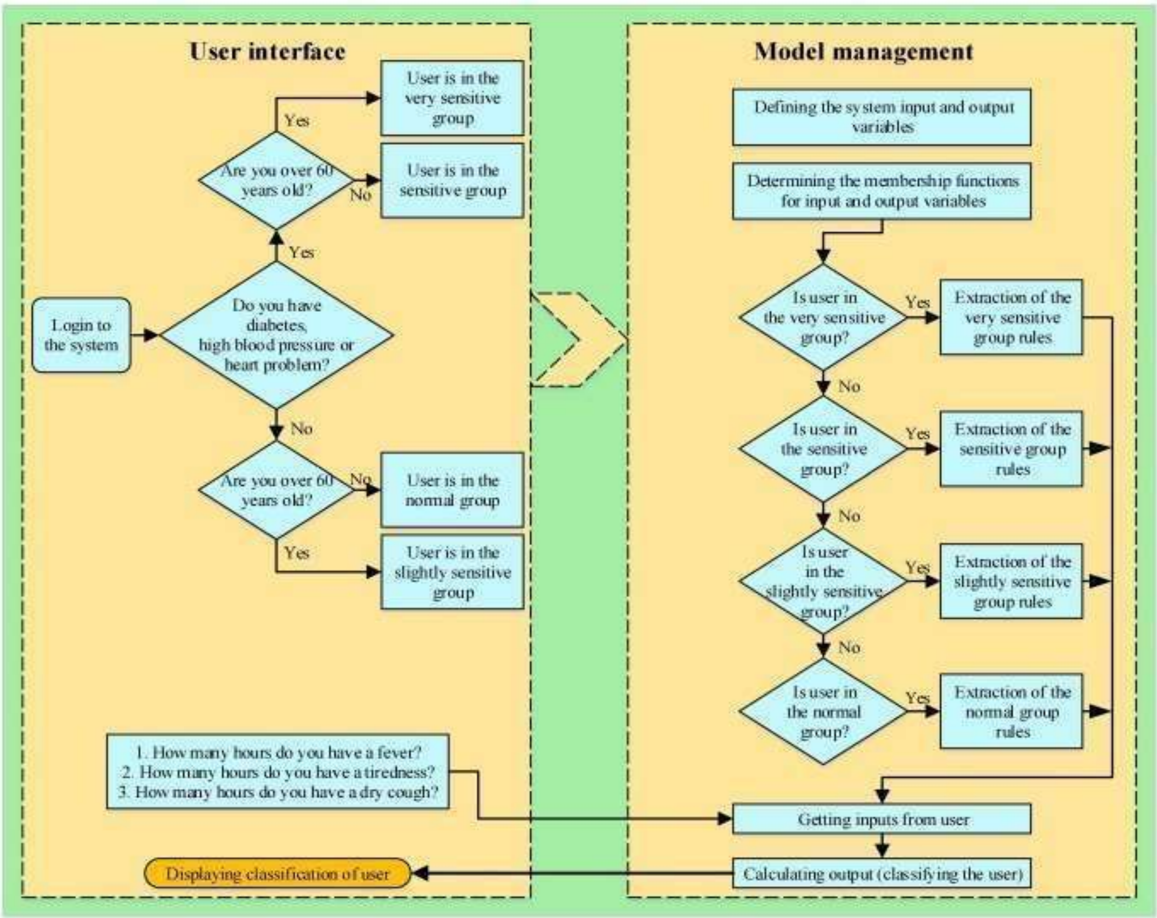


Fig. 2. The structure of proposed decision support system.

The Structure Of Proposed Decision Support System:

- **Step 1:** In this step, the assessment criteria of individuals' physical condition in the community is determined. According to the WHO reports, three criteria, namely fever, tiredness, and dry cough are the early symptoms of COVID-19. They are considered as the input variables of the FIS. In addition, the classification of the community members acts as the output variable of this system. Then, the membership functions of the input and output variables should be defined. The input variables consist of three membership functions, (low, mid, and high). The output variable is composed of five membership functions as follows:

- Class 1: Here, individuals who do not exhibit disease symptoms and have normal conditions are placed. These individuals are required to observe the healthcare tips and do their daily activities in accordance with the restrictions and guidelines set by their statesmen.
- Class 2: In this group, the individuals are placed who are suspicious of the disease and, thereby, should be quarantined and restricted in their relationship with others until their condition is identified although they may have a normal condition.
- Class 3: This group includes individuals who are suspected of having the mild disease and, in case they are proven to be infected, they do not need to be hospitalized and should be quarantined at home.
- Class 4: This group consists of members who are suspected of having a severe illness and need to be hospitalized if their disease is confirmed; however, they do not require intensive care.
- Class 5: This group contains those individuals who are suspected of suffering from serious illness and should be kept under intensive care in a hospital if their disease is proven.

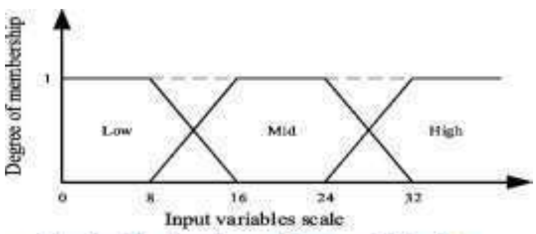
Based on the proposed membership functions, the assessed individuals fall into one of these five classes.

- **Step 2:** In this step, the fuzzy inference rules are determined by related experts and physicians for making a link between the input and output variables. It is noteworthy that a different set of fuzzy inference rules will be defined for each group of people in the society.
- **Step 3:** In this step, the community members are assessed. For this purpose, the user enters the system; then, the proposed FIS is activated for the groups after it is determined to which group the user belongs. Finally, the user is evaluated and classified by responding to three questions about fever, tiredness, and dry cough.

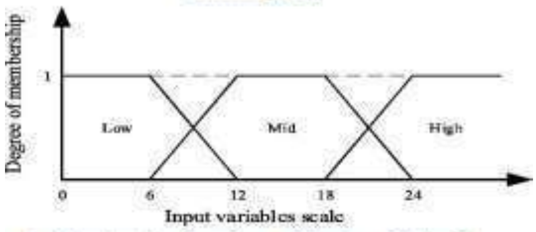
CASE STUDY

In this section, the performance of the proposed decision support system is evaluated using the latest WHO information on COVID-19 and physicians' knowledge in this domain. It should be noted that the evaluated criteria of the community members have been selected based on reports issued by the WHO; furthermore, physicians' knowledge has contributed to extract fuzzy inference rules and determine membership functions. The following presents a step-by-step implementation of the proposed approach:

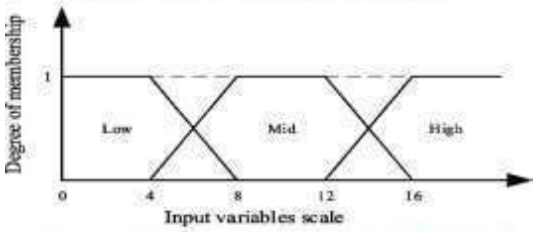
- **Step 1:** In this step, the input and output variables of the system are first determined. Fever, tiredness, and dry cough are defined as the input variables and the classification of community members is defined as the output variable of this system. Input variables entail the three membership functions of low, mid, and high; output variables include five membership functions (classes). It is also noteworthy that the membership functions of the input variables vary for different groups. In Fig. 3, the membership functions of the input variables have been presented for each group. The membership functions of the output variable are illustrated in Fig. 4.



a. Membership functions of input variables for normal group



b. Membership functions of input variables for slightly sensitive and sensitive groups



c. Membership functions of input variables for very sensitive group

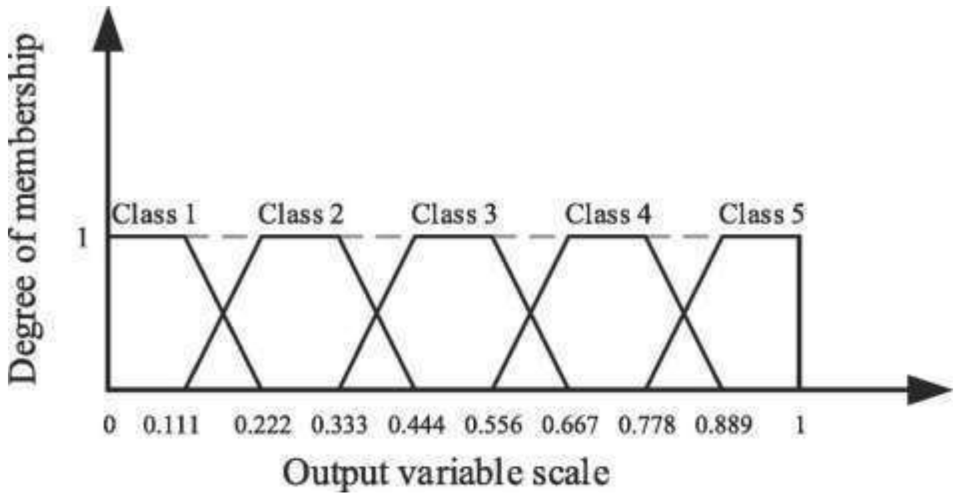
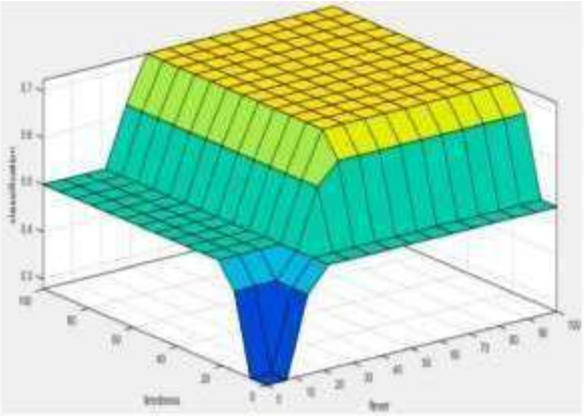
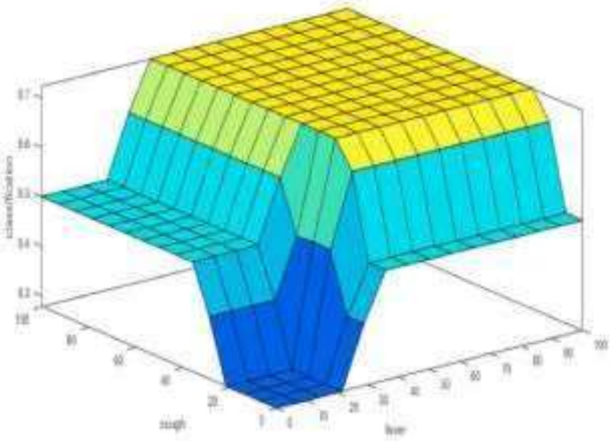


Fig. 4. Membership Functions Of Output Variables.

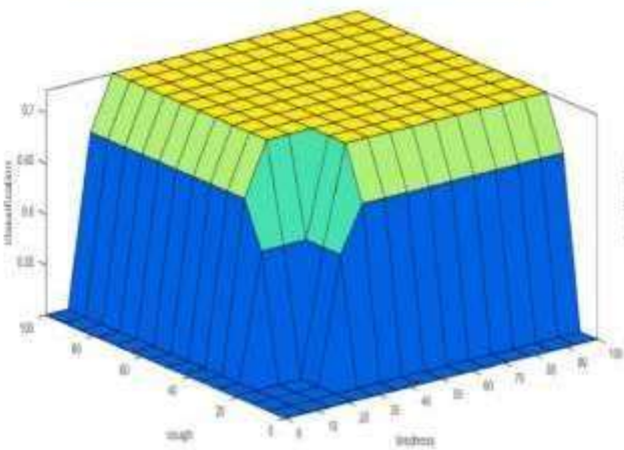
- **Step 2:** In this step, the fuzzy inference rules are determined by the physicians' knowledge for the four defined groups. The proposed FIS contains three input variables and three membership functions that have been defined for each input variable; therefore, there will be 3^3=27 fuzzy inference rules for each group of individuals. After the extraction of the fuzzy inference rules and their implementation in MATLAB R2016b software using FIS Editor GUI toolbox, one can observe the relationship between the input and output variables in the three-dimensional space. In Fig. 5, Fig. 6, Fig. 7, Fig. 8, the fuzzy inference rules have been shown in three-dimensional space for normal, slightly sensitive, sensitive, and very sensitive groups, respectively.



a. Relationship between fever, tiredness and classification

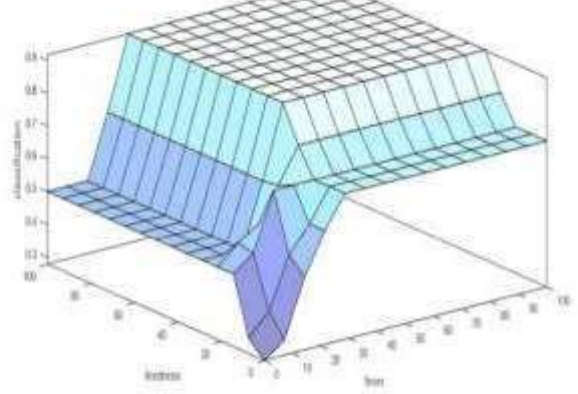


b. Relationship between fever, dry cough and classification

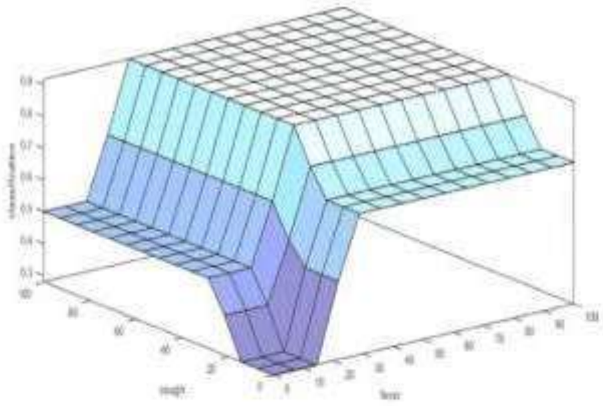


c. Relationship between tiredness, dry cough and classification

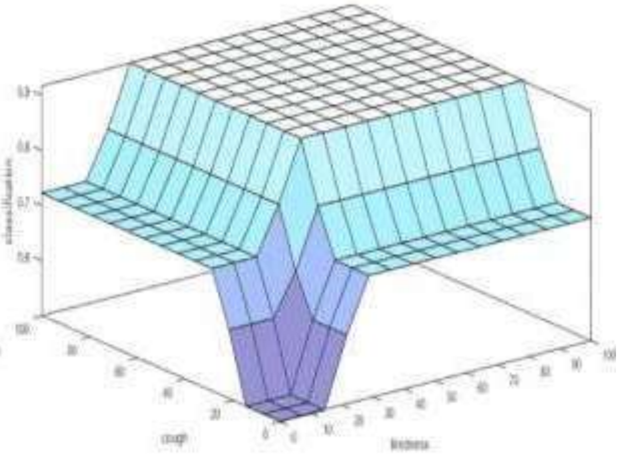
Fig. 5. Fuzzy Inference Rules For Normal Group



a. Relationship between fever, tiredness and classification



b. Relationship between fever, dry cough and classification



c. Relationship between tiredness, dry cough and classification

Fig. 6. Fuzzy Inference Rules For Slightly Sensitive Group.

- **Step 3:** In this step, the individuals in the society are classified. For this purpose, the following three questions are asked from the users:

- How many hours do you have a fever?
- How many hours do you have a tiredness?
- How many hours do you have a dry cough?

The responses obtained from these questions are considered as inputs in the rule viewer box of the FIS and, finally, the output is computed. The system output is always a value within the range of zero to one. If the value obtained as the output lies exactly in one membership function (class), the user will belong to that class. However, if the resulting number falls between two membership functions, then the membership degree is considered as the selection index. To this end, the membership degree of the output variable is calculated for both classes. If the membership degree is the same for both classes, it does not matter in which class it will be placed. But, if the membership degree for class A is greater than that for class B, it should be placed in class A. The following is an example illustrating the efficiency of the proposed approach.

Assume that there are four users as follows:

User 1: This user belongs to the very sensitive group.

User 2: This user belongs to the sensitive group.

User 3: This user belongs to the slightly sensitive group.

User 4: This user belongs to the normal group.

The answers given to the questions by each of these users are presented in Table 1.

Table 1. Responses to Questions by Each User.

Empty Cell	**User 1**	**User 2**	**User 3**	**User 4**
How many hours do you have a fever?	8	12	20	24
How many hours do you have a tiredness?	3	18	24	16
How many hours do you have a dry cough?	15	12	20	32

The values presented in Table 1 are considered as the inputs into the proposed FIS. The output variable value calculated for each user is reported in Table 2.

Table 2. Value of the output variable obtained from FIS for each user.

Empty Cell	**User 1**	**User 2**	**User 3**	**User 4**
Output value	0.662	0.51	0.509	0.502

For the classification of users, it is benefited from the results of Table 2 and the membership functions (classes) presented in Fig. 4. As it can be observed, the output value for user 1 is equal to 0.662. Although this value lies between classes 3 and 4 in Fig. 4, it has been placed on the right side of the intersection of the two classes; in other words, it has a tendency to class 4. Thus, user 1 will be placed in class 4. The output values for users 1, 2, and 3 are equal to 0.51, 0.509, and 0.502, respectively. According to Fig. 4, these values are only in class 3; hence, these three users belong to class 3.

SENSITIVITY ANALYSIS

In this section, four scenarios, based on changing the user groups, are used to assess the performance of the proposed approach. In the case study section, it was assumed that there were four users, each of whom belonged to one of the four defined groups. In the current section, to do the sensitivity analysis of the proposed approach, it is assumed that the desired user belongs to any of the other three groups. We strive to see which class the user will be placed in and whether or not the change of class makes sense. For this purpose, four scenarios are defined as follows:

Scenario 1:

In this scenario, it is assumed that user 1 does not belong to the very sensitive group and belongs to one of the other three groups. When user 1 is grouped in the very sensitive group, it would belong to class 4. The user is expected to fall into class 4 or a lower one if it is placed in other groups. This is so because the membership functions of input variables in the very sensitive group are denser with a higher slope than those in the other groups. On the other hand, the fuzzy inference rules have been considered more cautious for the very sensitive group. In Table 3, the output value and classification of each user are shown.

Table 3. Performance of the proposed approach if user 1 belongs to different groups.

Empty Cell	**Output value**	**class**
If user 1 belongs to very sensitive group	0.662	4
If user 1 belongs to sensitive group	0.356	2
If user 1 belongs to slightly sensitive group	0.356	2
If user 1 belongs to normal group	0.262	2

As it can be seen in Table 3, the obtained results are consistent with the claim made here; therefore, the performance of the proposed model is confirmed.

Scenario 2:

In this scenario, it is assumed that if user 2 belongs to any of the very sensitive, slightly sensitive, or normal groups, the classes this user belongs to will differ. The output value and classification of this scenario are presented in Table 4.

Table 4. Performance of the proposed approach if user 2 belongs to different groups.

Empty Cell	Output value	class
If user 2 belongs to very sensitive group	0.722	4
If user 2 belongs to sensitive group	0.51	3
If user 2 belongs to slightly sensitive group	0.51	3
If user 2 belongs to normal group	0.317	2

The results of this scenario are also in line with the logical expectations and reflect the accuracy of the proposed approach performance.

Scenario 3:

In this scenario, the performance of the proposed approach is measured when user 3 belongs to one of the groups other than the slightly sensitive group. In Table 5, the results of this scenario are presented.

Table 5. Performance of the proposed approach if user 3 belongs to different groups.

Empty Cell	Output value	class
If user 3 belongs to very sensitive group	0.916	5
If user 3 belongs to sensitive group	0.633	4
If user 3 belongs to slightly sensitive group	0.509	3
If user 3 belongs to normal group	0.5	3

The results obtained from this scenario also show that the model follows a reasonable trend and its performance is confirmed.

<u>Scenario 4</u>:

In this scenario, it is assumed that user 4 does not belong to the normal group and belongs to one of the other three groups. If this user belonged to the normal group, it would be placed in class 3. This user is expected to be placed in classes 3, 4, or 5 if it belongs to other groups. However, if a different result is obtained, it would indicate the inaccurate performance of the proposed approach. In Table 6, the results of this scenario are shown.

Table 6. Performance of the proposed approach when user 4 belonging to different groups.

Empty Cell	**Output value**	**class**
If user 4 belongs to very sensitive group	0.916	5
If user 4 belongs to sensitive group	0.722	4
If user 4 belongs to slightly sensitive group	0.722	4
If user 4 belongs to normal group	0.502	3

The results of this scenario and the other three scenarios illustrate the soundness and proper performance of the proposed approach. Since people above 60 years of age and those with heart disease, diabetes, or high blood pressure have a poor immune system, they are more vulnerable to COVID-19 and should be given more attention. Thus, the fuzzy inference rules and membership functions are defined for different groups in accordance with their vulnerability, which is clearly observed in the four proposed scenarios. In Scenario 3, for example, if user 3 belongs to the very sensitive group and COVID-19 test result is positive, he/she should be hospitalized and placed under intensive care. However, if the same user belongs to the sensitive group, he/she will be hospitalized but does not require intensive care. On the other hand, if he/she belongs to the slightly sensitive or normal groups, there is no need for his/her hospitalization, and he/she should spend his/her illness period in quarantine at home. Therefore, the results show that the proposed approach follows logical patterns and its performance is confirmed.

RESULT AND DISCUSSION

COVID-19 Testing in India

A rapid and sensitive diagnosis of the COVID-19 virus proved to be critical for infection prognosis and pandemic control. As per the Indian Council of Medical Research (ICMR), Govt. of India report, a total of 26,49,72,022 cumulative samples were tested up to 16th April 2021.

A total of 2,463 (1,233 government and 1,230 private) operational diagnostic laboratories were set up. Approximately 977/million individuals were tested daily and 13.20% of tests returned positive results showing high confirmed cases respective to the testing size, as WHO declared less than 5% positive rate is a good measure that infestation is under control.

Therefore, the rate of tests being carried out was not sufficient to monitor the pandemic properly and the actual number of infections could be far greater than the confirmed cases. As of 27th March 2022, India tested 78,69,22,965 samples with 4,30,19,453 confirmed cases . In the following sections, we discuss the tools and methods which have been adopted in India for COVID-19 testing.

Viral Antigen Detection

ICMR experimented with several plans to access the rate of transmission of infection, and out of them, one was a mass screening of suspected populations by rapid antigen test (RAT). As per the ICMR guidelines, RAT must be carried out before any confirmatory tests such as RT-PCR or CT scan for all the symptomatic and asymptomatic high-risk people residing in containment zones, hotspots, and entry points.

As of 26th April 2021, a total of 95 rapid antigen test kits were checked by ICMR for having a minimal critical acceptance scale of ≥ 50% (for sensitivity) and ≥95% (for specificity), and only 35 kits were found to be competent and approved for diagnostic uses .

Undoubtedly, antigen tests could have been a visionary step or game-changer to contain this lethal pandemic within countries where the infection had initially spread. But the earlier tests were not highly sensitive as compared to the tests that rely on the detection of viral RNA such as RT-PCR which can detect as low as 100 copies per ml of viral RNA from a sample.

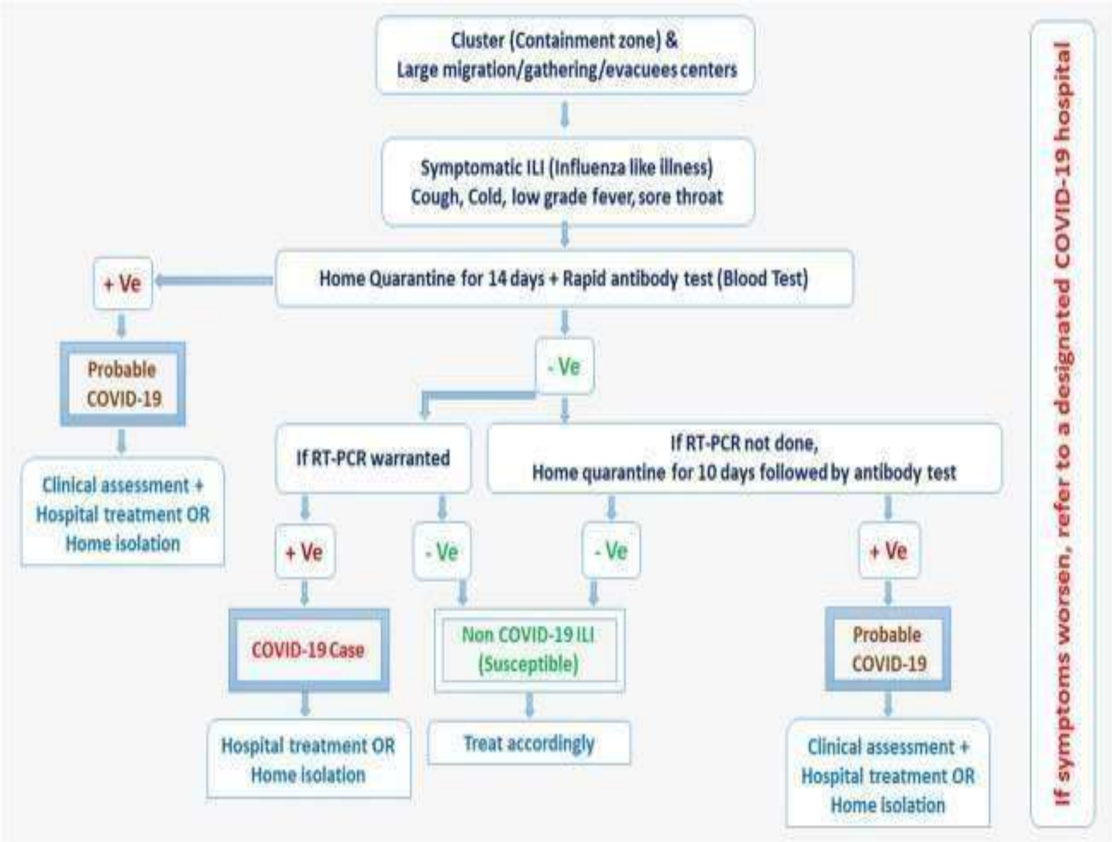
Viral Nucleic Acid Detection

Real-time reverse transcription-polymerase chain reaction (RT-PCR) assays were employed most widely in India for the etiologic diagnosis of the COVID-19 infection and are considered the gold standard. Until 28th April 2021, ICMR evaluated 346 local and internationally available RT-PCR kits and out of these 346 kits, only 162 kits met the expectations .

ICMR recommended RT-PCR test for all symptomatic individuals who undertook international travel in the last 14 days, contacts of laboratory-confirmed cases, health care workers, and patients with severe acute respiratory illness. The asymptomatic direct and high-risk contacts of confirmed cases were recommended to be tested once between day 5 and day 14 of coming in his/her contact (Figure 1).

SARS-CoV-2 had been mutating and several variants were reported worldwide such as Brazilian (17 mutations), South African (12 mutations), and British (17 mutations), which could not be identified separately using RT-PCR testing. Therefore, whole-genome sequencing of random 13,614 samples was also performed and screened for these mutations. Of these, 1,109 samples were tested positive for British, 79 for South African, and one for Brazilian variant. Fortunately, the molecular testing being done in India did not miss these mutations and the specificity and sensitivity of RT-PCR assays remained consistent as earlier.

Private RT-PCR testing cost approximately 3,000 Indian rupees (INR) during the first wave of the pandemic and certainly, was unaffordable for common people in a developing country like India. To minimize the RT-PCR cost and resources being utilized, ICMR, in alignment with WHO recommended a practical approach of pooled sample testing in regions having disease incidences less than 5%.



COVID-19 testing protocols released by government advisories of India (India, March 2022).

Serology Testing

Antibody-based serological detection assays received significant interest as an alternative to nucleic acid testing for COVID-19 diagnosis. Serological tests are based on the quantification of SARS-CoV-2 specific immunoglobulin IgM, IgG, and IgA generated by human B-lymphocytes upon exposure to the virus.

The advantage of immunological assays over the amplification assays was the ability to identify the previous infection history of individuals even though they never developed any symptoms. These assays helped healthcare professionals to produce data for those individuals who had overcome the disease and have generated an immune response against the pathogen.

Consequently, this data aided in determining the contact tracing for the individuals who may donate convalescent plasma, a possible treatment for acute sufferers and patients who seek medical attention due to low immune system activity [28–30]. On 4th April 2020, ICMR issued recommendations to initiate antibody-based testing for SARS-CoV-2 in clusters and large gatherings in different parts of India.

CT-Scan:

Lung computed tomography (CT) scan is a conventional and non-invasive viral detection tool that relies on X-rays transmission through the chest of the patient. In the case of COVID-19 diagnosis, perilobular pattern, reverse halo, air bronchograms, and consolidation were the potential characteristics in CT images that might provide 100% coverage.

As per ICMR findings, rapid antigen testing had only 40% sensitivity and RT-PCR assays had approximately 80% sensitivity in India, leaving behind a 20% uncertainty for remaining cases which might still spread the infection . So, regardless of radiation exposure, chest CT scanning was proposed as an option for diagnosing and monitoring COVID-19 infection in suspected cases where molecular testing failed.

Vaccination in India:

Mass vaccination was the main approach used by the government to ascertain immunity and protection in the general population.

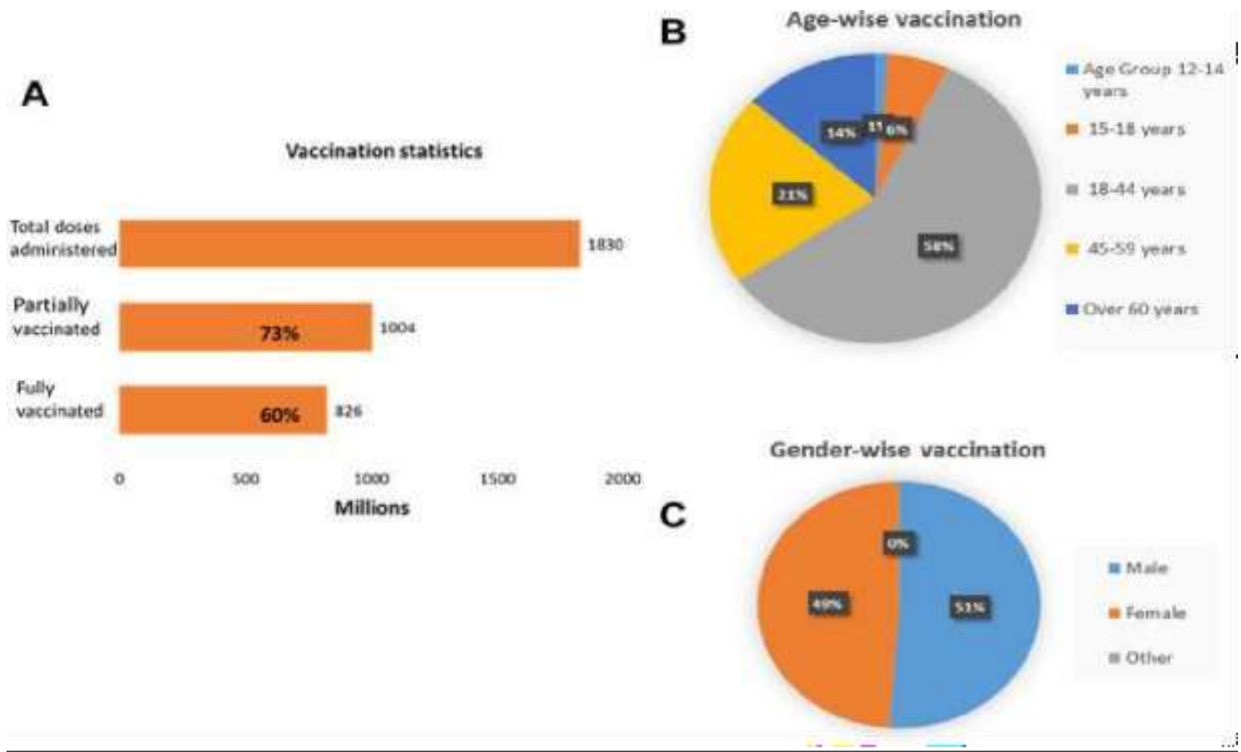
As of 27th March 2022, a total of 1,830,285,290 doses had been administered to eligible individuals in India. Out of it, 1,003,924,602 individuals received a single dose covering 73% of the population, while 826,360,688 were fully vaccinated representing 60% of the population [24, 32].

Table 2 depicts the list of approved vaccines in India and Figure 2 represents the vaccination status by 27th April 2022.

TABLE 2.

List of vaccines approved and in-use in India by 27 March 2022 [36, 41, 42, 44] (India, March 2022).

Vaccine	Status	Approval	Deployment
Covishield	In use	01 January 2021	16 January 2021
Covaxin	In use	03 January 2021	16 January 2021
Sputnik V	In use	12 April 2021	14 May 2021
Moderna	Approved	29 June 2021	Order cancelled
Johnson & Johnson	Approved	7 August 2021	Deliveries expected from October 2021
ZyCoV-D	Approved	20 August 2021	Deliveries expected from October 2021
Corbevax	Approved	28 December 2021	Not yet
Covovax	Approved	28 December 2021	Not yet
Sputnik Light	Approved	6 February 2022	Not yet



Vaccination dashboard of India.

(A) About 1,830 million doses have been administered so far. 1,004 million individuals are partially vaccinated and 826 million individuals are fully vaccinated.

(B) Age-wise distribution of vaccination.

(C) Gender-wise distribution of vaccination (India, March 2022).

Covaxin

India's first indigenous SARS-CoV-2 vaccine, Covaxin (BBV152), was developed and manufactured by Bharat Biotech (a Hyderabad-based pioneering biotechnology company) in association with the National Institute of Virology (NIV), Pune. India's homegrown vaccine showed 64% efficacy against asymptomatic cases, 93% against severe SARS-CoV-2 infection, 78% against symptomatic cases, and 65% against the newly emerged Delta variant .

On 2nd January 2021, BBV152 received permission for ―restricted emergency use‖ on the recommendation of the Central Drugs Standard Control Organization (CDSCO). However, this prompt emergency approval deprived of conducting Phase III studies drew widespread criticism regarding the vaccine efficacy and safety .

Receiving government approval on 25th November 2020, the company started Phase III trials and by the 3rd of July 2021, vaccine efficacy data were published in medRxiv pre-print . DCGI also agreed to Covaxin's clinical trials among the children group (2–18 years) and by that time, nearly 525 volunteers were registered in the study to be conducted at AIIMS Patna and Delhi .

This indigenous Indian vaccine gained authorization in some other nations such as Zimbabwe, Nepal, Philippines, Iran, Guyana, Venezuela, Guatemala, and Botswana . An *in vitro* preliminary study showed that the BBV152 has the potential to combat Alpha variant or lineage B.1.1.7, first identified in the United Kingdom.

The vaccine had shown efficacy in neutralizing lineage B.1.617 and Zeta variant or lineage P.2 (B.1.1.28) in investigations led by ICMR and NIV, Pune respectively . Recently, scientists of NIV, Pune collected the sera from the already vaccinated individuals and observed substantial efficiency of Covaxin in neutralizing Beta (B.1.351) and Delta (B.1.617.2) variants .

Covishield

Covishield, trade name for Oxford–AstraZeneca COVID-19 vaccine (ChAdOx1 nCoV-19, codenamed AZD1222) was developed by Oxford University and manufactured by Serum Institute of India, Pune .

Covishield, the made-in-India variant of AZD1222, was the prime vaccine adopted in India's mass immunization program and was the first vaccine to receive emergency use authorization approval by DCGI in early January 2021 .

A study conducted in 2020 showed that Covishield was 76% efficient in preventing symptomatic Coronavirus initially at 22 days after the first dose and 81.3% efficient following the second dose. .

Another study performed in Scotland reported that the efficacy of AZD1222 was 81% against lineage B.1.1.7 (alpha variant), and 61% against lineage B.1.617.2 (delta variant) . Following a homologous prime-boost strategy, India started a national immunization program against Coronavirus with two vaccines; covaxin and Covishield.

However, 18 persons, under the mass vaccination program, unintentionally received Covishield as the first dose and covaxin as the second dose. ICMR institutes along with AFMC (Armed forces Medical College, Pune) compared the immunogenicity profile and safety index of these 18 individuals (heterologous group) with 40 individuals (homologous groups) who received either covaxin or Covishield as both the doses.

They observed substantially higher IgG antibody concentration and neutralizing antibody response against the delta, beta, and alpha variants in the heterologous group as compared to homologous groups of either vaccine. This study proposed that a mixed immunization scheme such as using a viral vector-based vaccine followed by a dead virus-based vaccine could not be only the safe approach but also generates better immunogenicity .

Sputnik V

Sputnik V, also known as Gam-COVID-Vac, was the world's first registered viral vector vaccine developed by Gamaleya Research Institute of Epidemiology and Microbiology, Russia. On 12th April 2021, DCGI granted emergency use approval to Sputnik-V in India, and on 14th May 2021, the first dose was administered at Hyderabad .

Gam-COVID-Vac comprises two genetically modified E1 gene-deficient human adenoviruses: Ad26 and Ad5 which made them replication-defective. The interim analysis of a clinical phase-III trial conducted on 19,866 Russian volunteers showed that Sputnik V has 91.6% efficacy. In India, the original manufacturer joined hands with pharma giant Dr. Reddy's Laboratories, India for the marketing and distribution of Sputnik V.

As of 3 August 2021, Dr. Reddy's Laboratories received 3.15 million doses of the first component and 450,000 doses of the second component . The first component of the vaccine was being produced in substantial amounts easily. However, the second component was more volatile to produce. Therefore, its availability of it challenged the overall vaccine production process.

Consequently, makers of the standard vaccine developed a single-injection COVID-19 vaccine, i.e., Sputnik-Light. Sputnik-Light contains only the first component of Sputnik V (Ad26 vector) and is ideally suitable for more affected areas, permitting more individuals to be vaccinated rapidly.

A real-world study in Argentina involving participants of age 60–79 years showed 79% efficiency of Sputnik-Light in preventing infection and the same results were shown in phase III clinical trial conducted in Russia There were many other vaccines developed in China, the US and other countries, but we have discussed only those having a substantial share of the vaccination drive in India.

Vaccine Acceptance and Hesitancy

COVID-19 vaccines were the most needed invention, and several research and development institutions worldwide were working on it expeditiously. However, some studies raised concerns about the acceptance of COVID-19 vaccines in terms of safety, efficacy, efficiency, negative aftereffects, vaccine necessity, misalignment with the existing health system, and insufficient awareness of vaccine-treatable illnesses among the population .

Nevertheless, vaccine hesitancy had recurrently been the foremost restraining factor in the background of the present adverse socioeconomic and health consequences. Vaccine reluctance and negligence contributed to a considerable challenge in attaining the threshold for conferring COVID-19 population-level immunity. A study on 351 highly educated (85%) participants primarily of the age group 19–29 years (>75%) was conducted to investigate the beliefs associated with the SARS-CoV-2 vaccine and obstructions leading to vaccine hesitancy among the common Indian population .

The vaccination acceptance rate was observed to be satisfactory, with 86.3% of participants agreeing to get vaccinated as soon as it becomes available, whereas 13.7% of participants refused vaccination entirely. However, only 65.8% of the respondents got themselves vaccinated when the COVID-19 vaccine was available to them. In this survey, 64.4% raised concern about side effects, 20.2% showed worry about vaccine efficacy and 12% thought that the SARS-CoV-2 vaccine is certainly intriguing. The need of the hour was that everyone must realize that maximum vaccination coverage was indispensable globally to curtail the pandemic.

In the future, vaccine acceptance may improve through the development of trustworthy communication and information platforms to make general people aware of the benefits and availability of vaccines . Further, more scientific studies on the efficacy and safety of different Coronavirus vaccines and information about their availability through centralized sources would instill confidence and resolve concerns related to vaccine reluctance. Understanding the vaccine hesitancy and the factors involved would also be useful for policymakers in planning more competent strategies for the effective implementation of mass vaccination programs.

Impact on the Indian Economy

The pandemic had been largely disruptive to the Indian economy and could be considered as worse as the Great Depression of 1930 .According to the Ministry of Statistics of India, India’s growth for the fiscal year 2020 in the fourth quarter declined as low as 3.1% .

Undoubtedly, India had also been experiencing economic slowdown before the pandemic with deficits in consumption as well as demand. The existing pandemic certainly has further aggravated the pre-existing threats to the outlook of the Indian economy. The World Bank reviewed the country’s growth for the financial year 2021 with the bottommost figures as compared to the same in the last three decades since economic liberalization in 1990.

The gross domestic product (GDP) estimations were decreased even more to negative numbers, predicting a profound recession even after the government’s economic relief package to COVID-affected sectors in May 2020. As per the reports of the Nomura India Business Resumption Index, the Indian economic activity got down from 82.9 on 22nd March 2020 to 44.7 on 26th April 2020.

During the lockdown, approximately 140 million people became unemployed while salaries came down for countless others . During the first complete COVID-19 lockdown (21 days) in March

2020, the economy was estimated to lose more than USD 4.2 billion every day and only a quarter of the nation’s USD 2.8 trillion economic movements was effective .

A huge number of farmers across the nation who depend on perishable food items and daily-wage workers faced huge uncertainty in business and income. Major firms around the country such as Bharat Forge, Grasim Industries, Larsen & Toubro, Tata Motors, Aditya Birla Group, and BHEL reduced their operations or suspended temporarily while young startup businesses were also affected because their funding was stopped .

Indian stock markets suffered severe single (40% decline) and multi-day losses starting on March 23, 2020 . Interestingly, SENSEX and NIFTY posted their largest gains on March 25th, 1 day post the 21-day lockdown announcement by the government of India . On 26th March, the Indian government announced approximately USD 22 billion in economic relief funds for the poor to tackle food security, healthcare issues, and sector-related incentives.

The Asian Development Bank and World Bank also sanctioned funding to India to deal with the COVID crisis . The Department of Military Affairs withheld all the capital acquisitions and declared that the country will minimize the expensive defense imports . The Prime Minister of India announced a USD 260 billion economic stimulus package on 12 May 2020. Signs of recovery and rebound had shown by several economic indicators by July 2020 and the nation's economy was back to pre-COVID growth by December 2021 .

Discussion

The country was able to shut down its international borders within 4 weeks since the first case of COVID-19 was identified in the country, and a nationwide complete lockdown had been imposed since 25th March 2020. India's response to COVID-19 had been rated as one of the most rigorous across the world, surpassing Germany, Italy, the UK, the USA, and France by Oxford COVID-19 Government Response Tracker . It is estimated that India would have had 0.8 million Coronavirus cases by 15th April 2020 in the absence of a timely lockdown . Due to timely containment, the case number was restricted to 11,438 only as of 15th April 2020. ICMR had earlier sensed that stringent social distancing would decrease the cases by 62% . Likewise, a stochastic mathematical model forecasted that continuous transmission of the virus would have led to 3 million cases by end of the May but in actuality, there were only 138,845 cases reported in India by May 25th .

Additionally, the government of India established approximately 600 lab facilities all over the nation, even the railway department converted 375 train coaches into COVID-19 isolation wards [73]. All possible efforts had been made to aware the public of this threat *via* social media and broadcasting. Due to the limited availability of resources in the pandemic, Indian regulatory authorities recommend that there is no necessity to affirm the results by RT-PCR or CT-scan post RAT confirmation. Immediate RT-PCR is imperative if an antigen test comes negative in an asymptomatic patient.

India managed to control the transmission of the virus in the beginning but certain demographic and economic factors made it difficult to sustain the situation. One of the major hurdles was its population density which is almost 3-times that of China. The scenario became the worst in urban slum areas where population density is more than 250,000/km2 making physical distancing impossible. In India, about 140 million individuals are migrants and depend on daily-wage work therefore with the sudden imposition of complete lockdown, they were forced to go back to their native places without obeying the social distancing recommended by the government . Another key obstacle in India’s battle against SARS-Cov-2 had been the action and attitude of some of the residents; there had been reports of people hiding their travel history to escape from being quarantined. Some individuals took participation in forbidden massive religious meetings and became Coronavirus super-spreaders .

India’s poor pre-existing healthcare system is also responsible for the failure to some extent. Even though the healthcare setups had been strengthened instantly and about 2,000 dedicated COVID-19 amenities had been arranged across the nation over a very short period but the scarcity of doctors and trained nurses could not be fulfilled . The country holds just 0.8 doctors/1,000 individuals in comparison to Spain’s 4.1, China’s 2.36, Iran’s 1.1, Italy’s 4.1, and the USA’s 2.6 .

Furthermore, Odisha and West Bengal (eastern Indian states) had recently been devastated by a super cyclone—Amphan. Homeless people were rescued from this natural calamity and placed in common shelters where physical distancing was practically impossible. In the Laura Miller ranking system of healthcare, India received a ―CCC‖ ranking and was positioned farthest among the nine participating countries suggesting major improvements in the existing healthcare system.

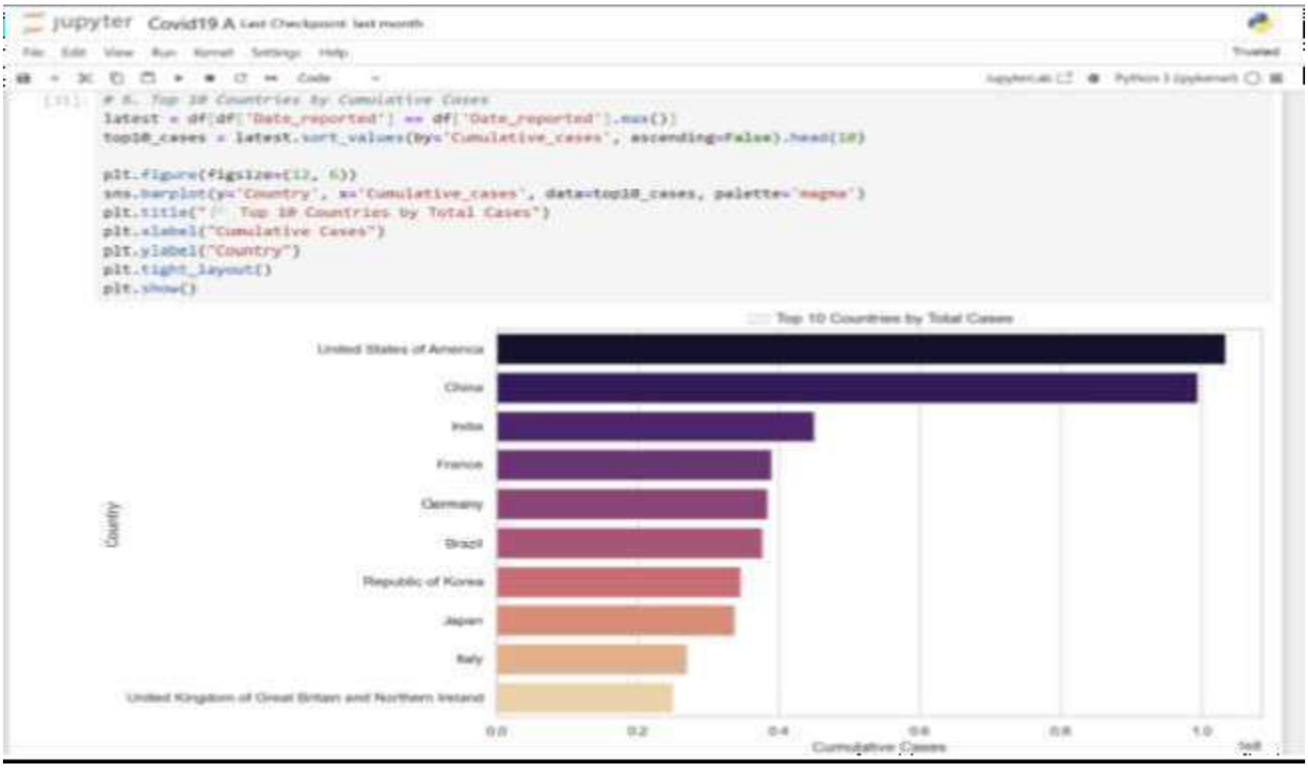
Since 2006, India spends almost 3.5% of its GDP on health and it is half of the GDP of the world expended by WHO members and by BRICS nations . But the Central Bureau of Health Intelligence observed that there is just 1.28% of the government’s public expenditure (GPE) of the total revenue of the government, concluding that out-of-pocket and private health expenditures are extremely high .

As per National Sample Survey Office 2013–2014, out-of-pocket expenditure is a persistent concern in India as it is about 65% of the total health spending. According to an OECD study, India owns 0.5 hospital beds/1,000 residents as compared to China’s 4.3 hospital beds/1,000 residents , indicating the need for prompt and major improvements in the public healthcare system. Another challenge faced by India during this pandemic was a short supply of goods for pharma companies.

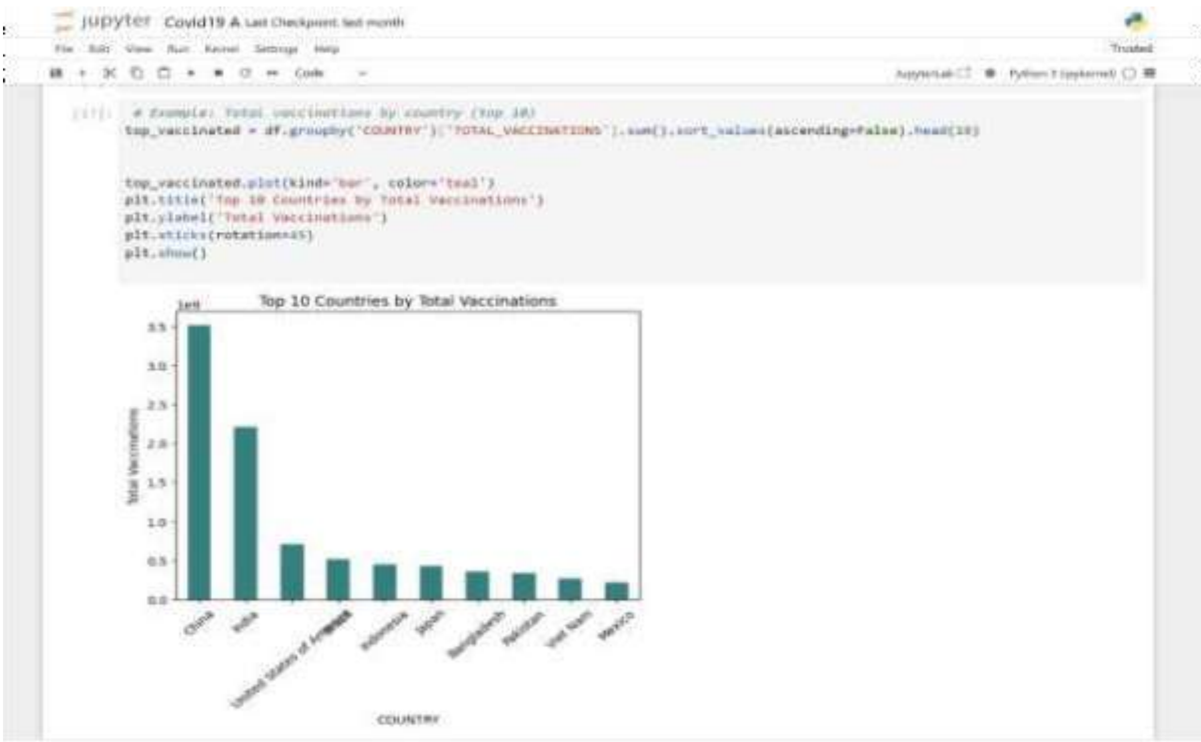
The nation used to import about 70% of the active pharmaceutical ingredients (API) for the drugs manufactured by Indian pharmaceutical companies. This huge dependency left the Indian pharma industry helpless in maintaining the supply chain as China suspended all the production facilities in the COVID-19 pandemic. Consequently, this temporary shortage of API led to a hike in the price of basic medicines and supplements such as penicillin, paracetamol, and vitamins. The lesson we learned is that being one of the largest countries, India should incentivize the pharma sector to enhance the production of API which will reduce the nation’s dependency on Chinese imports and reinforce national security.

SCREENSHOTS

❖ Top 10 Countries by Total Case:-

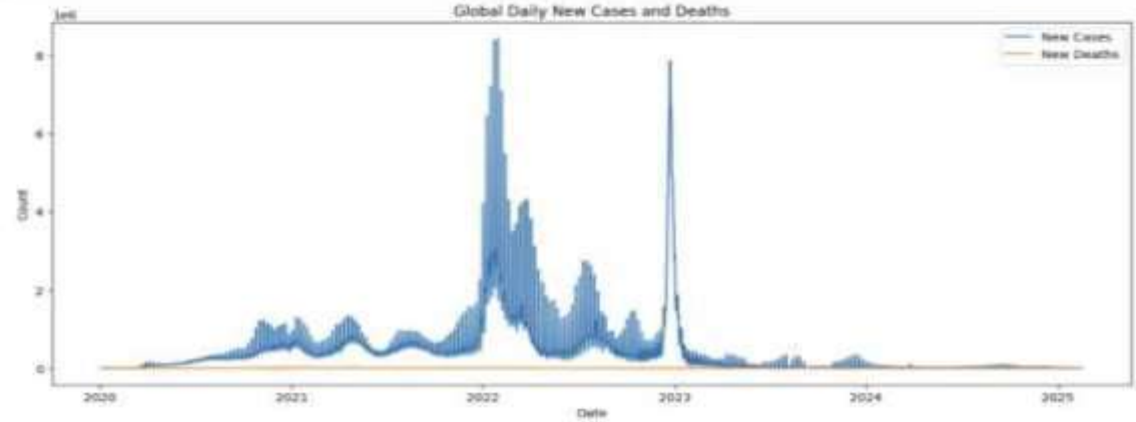


❖ Top 10 Countries by Total Vaccination:-



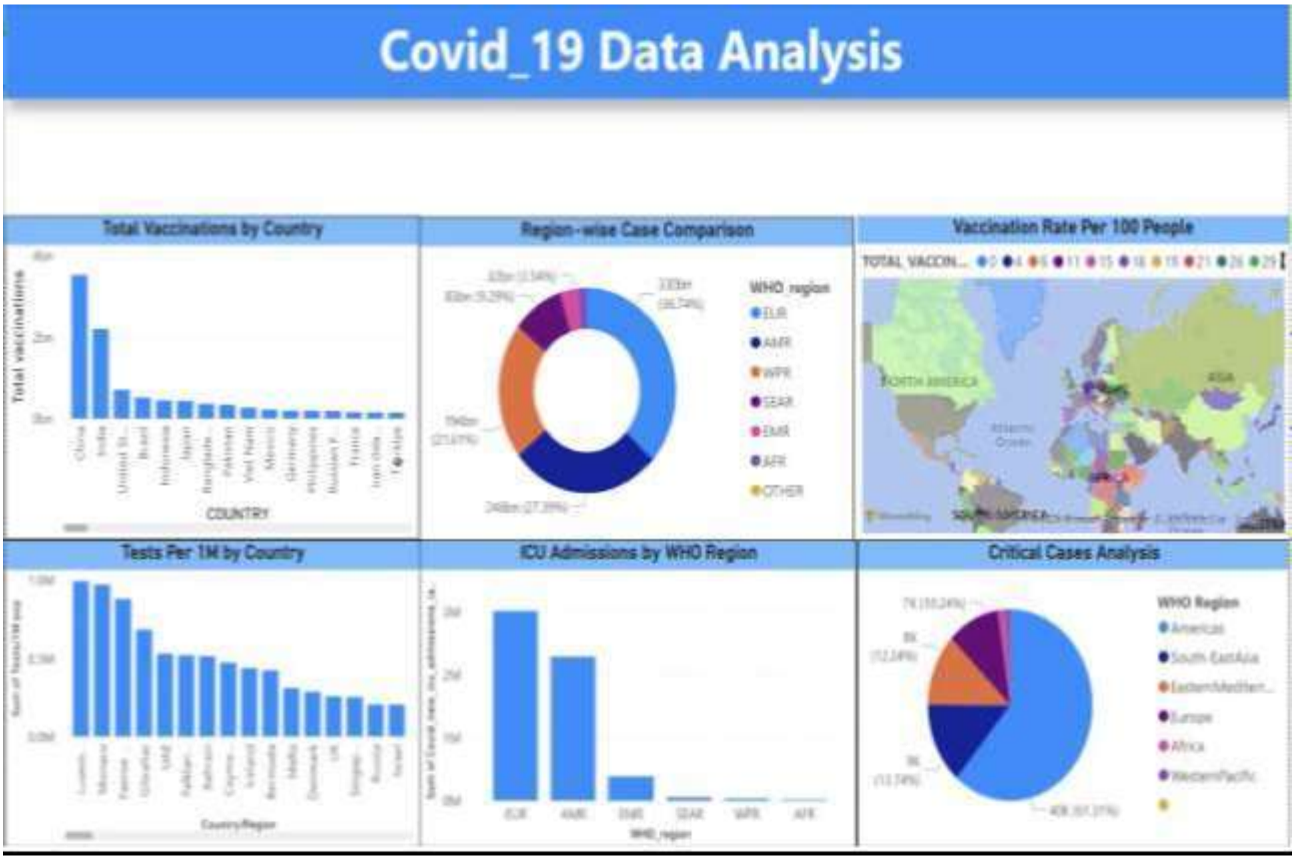
❖ Global Daily New Cases and Deaths:-

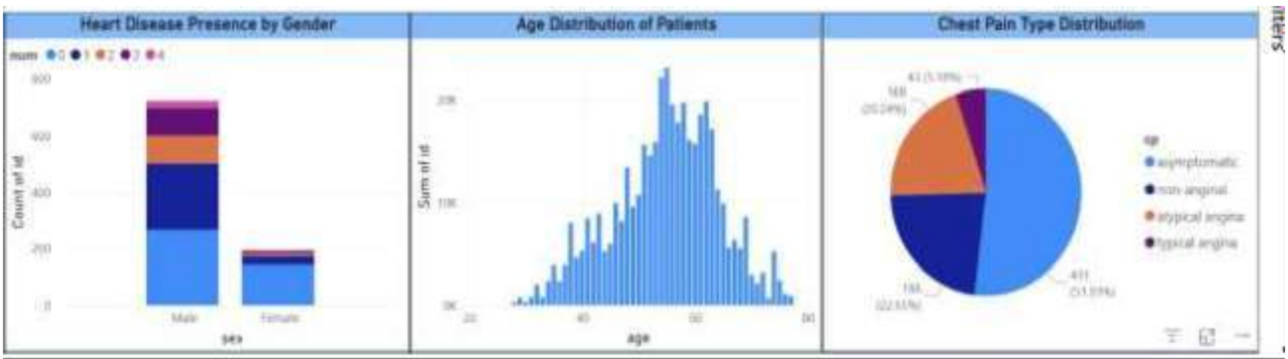
```
[10]: global_daily = df.groupby('Date_reported')[['New_cases', 'New_deaths']].sum().reset_index()

# Plotting
plt.figure(figsize=(15, 6))
sns.lineplot(data=global_daily, x='Date_reported', y='New_cases', label='New Cases')
sns.lineplot(data=global_daily, x='Date_reported', y='New_deaths', label='New Deaths')
plt.title("Global Daily New Cases and Deaths")
plt.xlabel("Date")
plt.ylabel("Count")
plt.legend()
plt.show()
```

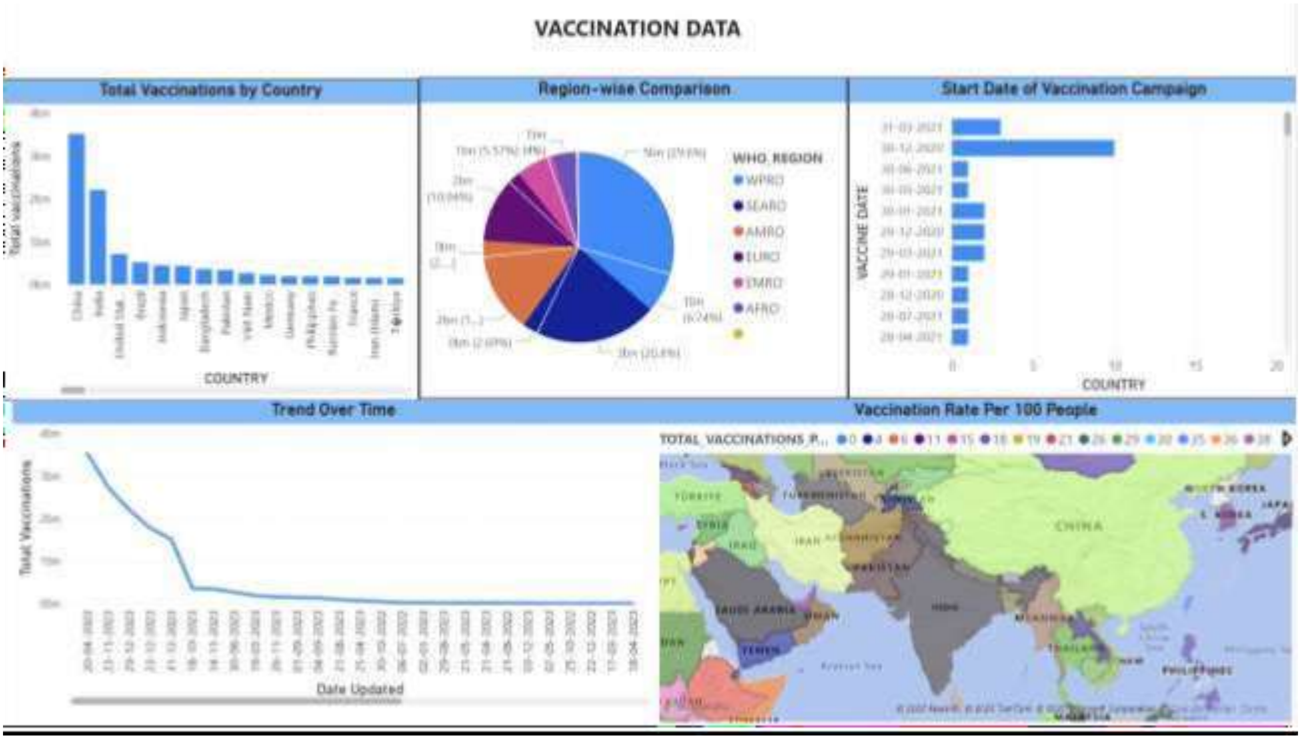


POWER-BI

SCREENSHOTS






VACCINATION DATA
Total Vaccinations by Country
Total Vaccinations
COUNTRY
Region-wise Comparison
WHO_REGION
WPRO
SEARO
AMRO
EURO
EMRO
AFRO
Start Date of Vaccination Campaign
VACCINE DATE
COUNTRY
Trend Over Time
Total Vaccinations
Date Updated
Vaccination Rate Per 100 People
CHINA

CONCLUSION

In this paper, a practical decision support system was proposed to classify community members and, accordingly, manage the demand and control the epidemic outbreaks in the healthcare supply chain. In the proposed approach, users are first grouped according to two criteria, age range and pre-existing diseases (such as diabetes, heart problems, or high blood pressure). These users are then classified using FIS. It should be mentioned that the three criteria of fever, tiredness, and dry cough have been used to classify users and different membership functions of these variables have been considered for various groups. Finally, the proposed approach was validated using data pertaining to the four users. These results, and the results of the sensitivity analysis process, indicate the proper and effective performance of the proposed approach.

Besides its benefits, any research may suffer from some limitations and this paper is no exception. One of the limitations of the current study is that the three symptoms of fever, tiredness, and dry cough have been considered as the criteria for the assessment of community residents. These three criteria do figure among the most common symptoms of COVID-19 infection, but other symptoms, such as diarrhea, vomiting, and the like have also been observed in some patients (Huang et al., 2020, Rothan and Byrareddy, 2020, Wang et al., 2020). In this paper, three membership functions have been considered for input variables where it is possible to promote the accuracy of the decision support system by increasing the number of membership functions. Thus, for future research, it is recommended that other criteria such as diarrhea, vomiting, etc. be added to input variables in order to design a more accurate decision support system and to increase the number of membership functions of input and output variables as well. In this paper, an expert-based approach was employed to control epidemic outbreaks. It is recommended to use the integrated data science and expert knowledge to propose an adaptive neuro-fuzzy inference system for the control of epidemic outbreaks. Moreover, the decrease of the disruptions caused by epidemic outbreaks in supply chain network design by using multi-stage/scenario-based stochastic programming model can be an interesting and practical topic to be explored in future works (Govindan et al., 2017; Fattahi et al., 2018, Fattahi and Govindan, 2018). In epidemic disasters, the availability of vast amounts of data is usually evident. The employment of disruptive technologies can be a useful tool in this area (Choi et al., 2020a, Choi et al., 2020b, Shen et al., 2019, Ting et al., 2020; Govindan et al., 2018).

India went through one of the biggest sufferings during the COVID-19 pandemic. The pandemic posed extensive health and socioeconomic challenges and also became the largest disruption in the Indian economy. In summary, we observe the major reasons behind the COVID-19 pandemic in the Indian context, to identify the pitfalls in the public healthcare system and economic preparedness to tackle a pandemic situation. We further highlight the role of citizens in aiding the fight against this kind of national or global disaster by obeying the government advisories of social distancing and containment.

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Data Engineering with AI & Analytics: COVID-19 Data

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Abstract: The COVID-19 pandemic posed unprecedented challenges to global health systems, economies, and societies, demanding rapid and innovative responses. In this context, Artificial Intelligence (AI), data analytics, and data engineering emerged as vital tools for understanding and managing the crisis. This research paper examines how these technologies were deployed to monitor virus transmission, predict future outbreaks, allocate resources, and support evidence-based decision-making. By integrating structured and unstructured data from authoritative bodies such as the World Health Organization (WHO), national health agencies, and non-traditional sources like mobility and social media data, researchers were able to derive meaningful insights through machine learning and analytical models. Furthermore, data engineering played a foundational role in enabling seamless data integration, processing, and access, supporting scalable analytical workflows. The application of AI-driven forecasting and visualization tools enabled real-time dashboards and predictive simulations, which significantly influenced global and local health policies. This study underscores how technological innovation—when grounded in ethical principles and robust infrastructure—can empower societies to navigate complex public health emergencies more effectively.

I. INTRODUCTION

COVID-19, caused by the novel coronavirus SARS-CoV-2, emerged in late 2019 and quickly evolved into a global pandemic, disrupting daily life and overwhelming health systems worldwide. With millions of lives lost and widespread social and economic impact, the crisis highlighted the critical need for fast, reliable, and data-informed responses. Traditional public health methods—while essential—were insufficient on their own to track and contain the rapid spread of the virus. To complement these efforts, a suite of advanced digital technologies, particularly AI, machine learning, and data engineering, were adopted to enhance the pandemic response.

This paper explores how these technologies revolutionized the understanding and management of COVID-19. From enabling early outbreak detection to guiding resource allocation and vaccine deployment, data-driven approaches offered a new lens through which to interpret the pandemic. The integration of technology in public health operations marked a turning point, emphasizing the need for resilient digital infrastructure and interdisciplinary collaboration in combating future health threats. By examining key data sources, technical methods, analytical models, and ethical implications, this study presents a comprehensive overview of how AI and data systems shaped global responses to the COVID-19 pandemic.

II. DATA SOURCES AND COLLECTION

Effective pandemic response efforts relied on the timely collection, validation, and analysis of high-quality data. The pandemic spurred unprecedented data generation across sectors, necessitating robust frameworks for data sourcing and management. The primary data sources included:

- **World Health Organization (WHO)**: Served as the central global authority providing standardized epidemiological reports, case counts, mortality statistics, vaccination progress, and public health advisories.
- **National Public Health Agencies**: Institutions like the Centers for Disease Control and Prevention (CDC) in the United States, the Ministry of Health and Family Welfare (MoHFW) in India, and the European Centre for Disease Prevention and Control (ECDC) in Europe provided localized data, often at higher granularity, including hospital capacity, testing rates, and community transmission levels.
- **Non-Traditional Data Sources**: Social media platforms (e.g., Twitter), mobility tracking tools (e.g., Google Mobility Reports, Apple Maps), and digital health applications offered insights into human behavior, movement patterns, symptom self-reporting, and public sentiment. These unconventional datasets provided valuable context for interpreting traditional metrics.

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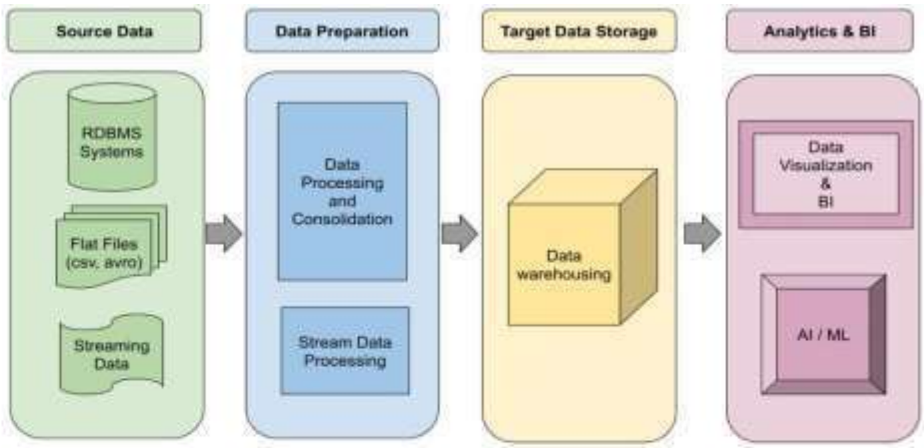
The heterogeneous nature of these data sources—differing in structure, update frequency, and quality—made data engineering an indispensable component of COVID-19 data science.
persist.

III. DATA ENGINEERING: ETL PROCESSES

The backbone of any data analytics effort is the Extract, Transform, Load (ETL) pipeline, which prepares raw data for effective analysis. In the case of COVID-19, data engineering ensured that large volumes of data from disparate sources were made coherent, clean, and analysis-ready.

- **Extraction:** Data ingestion involved API integrations, automated web scraping, and retrieval from government repositories. Many datasets were updated daily or even hourly, requiring automation for timely access.
- **Transformation:** Once extracted, data underwent rigorous cleaning and standardization. Key tasks included handling missing values, aligning disparate metrics (e.g., deaths per 100,000 vs. absolute counts), harmonizing time zones, and normalizing dates across countries with differing reporting standards.
- **Loading:** Processed data was loaded into relational databases (e.g., PostgreSQL), cloud storage systems (AWS S3, Google Cloud Storage), or data lakes for long-term storage. Tools such as Apache Airflow orchestrated these pipelines, while platforms like Snowflake and BigQuery enabled scalable storage and querying.

Without these processes, integrating global data at scale would have been infeasible. ETL not only improved data quality and accessibility but also reduced latency, enabling real-time monitoring and faster public health reactions.



IV. DATA ANALYSIS WITH AI AND MACHINE LEARNING

The application of AI and machine learning was central to extracting actionable insights from COVID-19 data. These methods were used across multiple domains, including epidemiology, logistics, and public policy.

- **Trend Analysis**: Time-series forecasting models (ARIMA, Prophet, LSTM networks) predicted infection waves, seasonal fluctuations, and the impact of interventions. These insights informed lockdown decisions and healthcare preparedness.
- **Risk Factor Modeling**: Supervised learning algorithms, such as logistic regression, random forests, and gradient boosting machines, identified populations at greater risk of severe illness based on age, pre-existing conditions, socioeconomic factors, and occupation.
- **Clustering and Pattern Discovery**: Unsupervised learning (e.g., K-means clustering, hierarchical clustering) grouped regions or demographic profiles based on transmission patterns, aiding localized containment strategies.
- **Spatial Mapping and GIS**: Geospatial AI techniques overlaid infection data with geographic, demographic, and socioeconomic factors to visualize disease spread and resource needs, enabling more equitable interventions.

The flexibility of AI enabled rapid adaptation to evolving data, offering continuous learning and adjustment as new variants and public behavior patterns emerged.

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V. VISUALIZATION TECHNIQUES

Effective communication of data insights was as critical as the analysis itself. Visualization tools helped translate complex information into accessible formats for public officials, researchers, and the general population.

- **Line Charts and Bar Graphs**: Tracked daily trends in new cases, fatalities, recoveries, and testing rates.
- **Heat Maps and Choropleths**: Illustrated regional infection intensity, mobility changes, and vaccine coverage, often layered with socioeconomic indicators.
- **Interactive Dashboards**: Platforms like the Johns Hopkins University COVID-19 Dashboard and Microsoft's Bing COVID-19 Tracker provided real-time updates with customizable views, filters, and global comparisons.
- **Animation and Timelines**: Animated visualizations captured the temporal evolution of the virus, enabling better understanding of global spread and intervention effectiveness.

Visualization libraries such as D3.js, Plotly, Matplotlib, and Seaborn, as well as business intelligence tools like Power BI and Tableau, played vital roles in delivering these outputs

VI. PREDICTIVE MODELING AND FORECASTING

Forecasting models enabled governments and healthcare providers to anticipate challenges and plan accordingly.

- **Scenario Modeling:** Epidemiological models like SEIR (Susceptible-Exposed-Infectious-Recovered) simulated outcomes under different intervention strategies, helping to evaluate the efficacy of masks, school closures, and vaccination campaigns.
- **Early Warning Systems:** Anomaly detection algorithms flagged unusual spikes in syndromic or social media data, triggering targeted investigations and responses.
- **Healthcare Resource Planning**: Predictive models forecasted ICU occupancy, ventilator demand, and PPE supply shortages. These models proved crucial in resource-limited settings, helping to avoid catastrophic system overloads.

The integration of real-time data streams into forecasting pipelines created adaptive systems capable of responding dynamically to the pandemic's evolving landscape.

VII. DISCUSSION AND FUTURE DIRECTIONS

The pandemic revealed both the power and limitations of data-driven health systems. Moving forward, several priorities should guide future preparedness:

- **Global Collaboration:** Standardizing data formats, sharing protocols, and creating international data-sharing agreements would accelerate coordinated responses.
- **Infrastructure Investment:** Strengthening cloud infrastructure, expanding digital health records, and increasing computational resources will be essential for future scalability.
- **Multimodal Data Integration:** Fusing clinical data with social, environmental, and behavioral signals can create more holistic models of disease spread and population health.
- **Continuous Innovation:** Encouraging open-source contributions, academic-industry collaborations, and agile development cycles can sustain progress in digital epidemiology.

By embedding these principles, societies can better navigate both endemic COVID-19 and future health crises.

VIII. CONCLUSION

The COVID-19 pandemic catalyzed a global shift toward data-driven public health strategies. The integration of AI, data analytics, and engineering provided critical tools for rapid detection, real-time monitoring, and predictive planning. These technologies helped flatten curves, save lives, and inform public behavior during a time of deep uncertainty. As we transition into a post-pandemic world, the lessons learned underscore the value of continued investment in digital infrastructure, interdisciplinary research, and ethical innovation. A future grounded in intelligent, equitable, and transparent data systems is not only desirable but necessary for global health security.

The intersection of AI, analytics, and data engineering proved invaluable during the COVID-19 pandemic. These technologies facilitated efficient data processing, timely insights, and informed decision-making. As the world navigates a post-pandemic future, embracing data-driven methodologies will be essential in building resilient, responsive, and equitable health systems.

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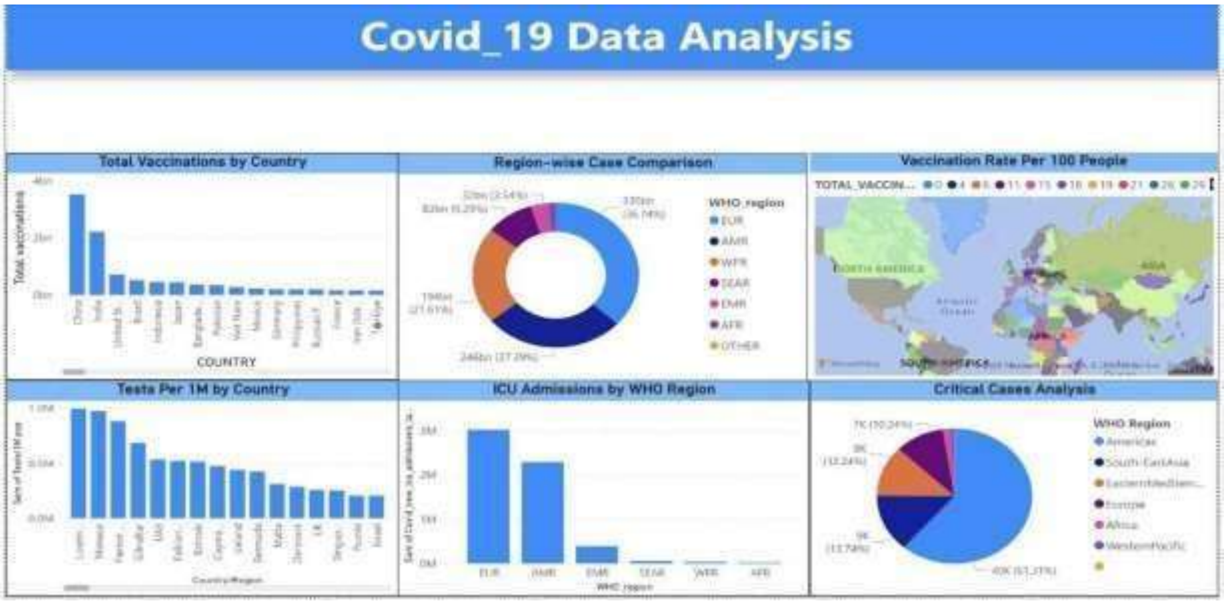

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