[1]Swathi Buragadda,

[2]Gangavarapu Mohana Rao

[3]M. Lavanya,

[4]Adapa Gopi,

[5]Panduranga Ravi Teja

# Development and Impact Analysis of a Multi-Pandemic Real-Time Data Dashboard: A Comparative Analytical Approach

Journal of Electrical Systems

***Abstract***: This research presents the development and implementation of a Multi Pandemic Real-Time Data Dashboard, designed to facilitate enhanced comparative analysis across various global pandemics. Utilizing a combination of real-time data acquisition, statistical modeling, and predictive analytics, the dashboard provides a dynamic platform for analyzing pandemic trends and outcomes. Our methodology involved integrating diverse data sources, employing mathematical models such as the SIR (Susceptible, Infected, Recovered) model and machine learning algorithms for data processing and trend prediction. Key findings indicate that the dashboard effectively identifies patterns in pandemic spread and impact, offering valuable insights for public health decision-making. The research underscores the significance of advanced data analytics in managing public health crises, highlighting the dashboard's potential in aiding proactive pandemic response and policy formulation.

**Keywords**: pandemics, SIR, COVID-19, Time Series Epidemic Forecasting (TSEF)

## I.Introduction

The integration of technology in various sectors has revolutionized the way we collect, analyze, and interpret data. This is particularly evident in the realm of public health, where the advent of real-time data dashboards has significantly enhanced our ability to monitor and respond to pandemics. In our study, we focus on the development and analysis of a Multi-Pandemic Real-Time Data Dashboard, a sophisticated tool designed to provide comprehensive insights into pandemic trends and assist in public health decision-making and policy formulation.

The impetus for this study stems from the challenges faced during recent global health crises, where the rapid spread of infectious diseases underscored the need for real-time data monitoring and analysis. Traditional methods of data collection and analysis often lagged behind the fast-paced developments of pandemics, leading to delays in response and mitigation strategies. Recognizing this gap, our study aims to develop a dashboard that not only tracks real-time data but also offers predictive insights through advanced statistical models and machine learning algorithms.

The core of our methodology involves the meticulous gathering of data from reliable sources. This data encompasses key metrics such as infection rates, recoveries, and fatalities from multiple pandemics, ensuring a comprehensive dataset that forms the backbone of our analysis. The diversity and volume of this data present unique challenges in terms of integration and processing. To address these challenges, we employ the Susceptible, Infected, Recovered (SIR) model, a standard epidemiological model that helps in understanding the spread of diseases. Additionally, we integrate advanced machine learning algorithms to provide predictive analytics, offering foresight into potential future trends and enabling proactive measures.

A distinctive feature of our dashboard is its emphasis on user interaction and customization. Recognizing that different users may have varying needs and perspectives, we designed the dashboard to be highly interactive and customizable. Users can filter and visualize data across various parameters such as date range, region, and demographic factors. This level of customization not only enhances the user experience but also allows for more targeted and relevant analysis, catering to the specific needs of public health officials, researchers, and policymakers.

Another critical aspect of our dashboard is the incorporation of real-time data updating features. In the context of a pandemic, conditions can change rapidly, and having up-to-date information is crucial for effective decision-making. Our dashboard is equipped with mechanisms to continuously update data, ensuring that it reflects current conditions and trends. This feature is particularly important for public health officials and policymakers who rely on the latest data to make informed decisions.

The development of our Multi-Pandemic Real-Time Data Dashboard represents a significant step forward in the field of public health informatics. By leveraging the power of data analytics and machine learning, we have created a tool that not only provides real-time insights into pandemic trends but also facilitates a comparative analysis across different pandemics. This comparative aspect is particularly valuable, as it allows for the identification of patterns and correlations that may not be apparent when examining a single pandemic in isolation.

Our methodology culminates in a robust tool that serves multiple purposes. For public health officials, it offers a reliable and up-to-date source of information that can inform response strategies and resource allocation. For researchers, it provides a rich dataset for epidemiological studies and model validation. For policymakers, it serves as a basis for formulating evidence-based policies and measures to combat pandemics.

In conclusion, our study contributes significantly to the field of public health by providing a sophisticated tool for monitoring and analysing pandemic data. The Multi-Pandemic Real-Time Data Dashboard stands as a testament to the power of technology and data analytics in enhancing our understanding and response to global health crises. As we continue to face challenges posed by infectious diseases, tools like our dashboard will be instrumental in guiding our efforts to safeguard public health and well-being.

## II.Literature Review

The recent advancements in various fields, as reflected in the literature, demonstrate a significant shift towards the integration of technology and data analytics in diverse domains. This literature survey encapsulates the essence of these developments across different studies.

Jiang et al. [1] delve into the complexities of microbiome multi-omics network analysis, highlighting the statistical considerations, limitations, and opportunities in this field. Their work underscores the intricate balance between methodological rigor and the practical challenges in microbiome research, offering insights into the potential of multi-omics approaches in understanding complex biological systems. In the realm of real estate, Mal kowska [2] explores the impact of technology on the business landscape, particularly in European Union countries. This comparative analysis sheds light on how technological advancements are reshaping the industry, influencing everything from property management to customer engagement strategies. Brown's study [3] focuses on the educational sector, examining how faculty in large lecture courses utilize learning analytics dashboard data. This research provides a unique perspective on the intersection of technology and education, revealing how data-driven insights can enhance teaching methodologies and student engagement in large-scale educational settings. De Lusignan et al. [4] present a protocol for improving the management of atrial fibrillation in general practice. Their mixed-methods study emphasizes the need for robust protocols in healthcare, especially in managing complex conditions like atrial fibrillation, and highlights the potential of integrating various research methodologies to achieve this goal. Burningham et al. [5] discuss the equipped medication dashboard, a tool designed to enhance the quality of prescribing practices for older veterans. This study evaluates the dashboard as an alternative to traditional methods, such as in-person academic detailing, demonstrating the potential of digital tools in improving healthcare outcomes. Further exploring the healthcare domain, de Lusignan et al. [6] evaluate an atrial fibrillation dashboard using the Think Aloud protocol. This research underscores the importance of user-centered design and evaluation in healthcare technology, ensuring that such tools are both effective and user friendly. Richter Lagha et al. [7] focus on the usability testing of a potentially inappropriate medication dashboard. Their work is a critical component of the dashboard development process, emphasizing the need for rigorous testing to ensure the tool's effectiveness and user satisfaction. Lee et al. [8] present an online time-to-event dashboard for comparing the control of COVID-19 among continents. This observational study utilizes an innovative approach to track and compare pandemic responses, offering valuable insights into public health strategies across different regions. De Lusignan et al. [9] again contribute to the field of healthcare with their protocol for managing atrial fibrillation in general practice. This study mirrors their earlier work [4], reinforcing the importance of comprehensive protocols in healthcare. Mal kowska et al. [10] extend the discussion on digital transformation, examining its impact on European countries. Their comparative analysis provides a broader understanding of how digitalization is influencing various sectors across Europe. Lee et al. [11] continue their exploration of COVID-19 control measures with a focus on the effective management of the pandemic. Their study employs a unique methodological approach, offering a comparative perspective on pandemic management strategies. Lamm et al.

[12] discuss the implementation of cyberlearning tools in large introductory courses in chemical engineering. This study highlights the transformative potential of digital tools in enhancing educational experiences and outcomes. Rasool [13] introduces a real-time autonomous gas analyzer for soils, a significant advancement in environmental monitoring technology. This innovation represents the intersection of technology and environmental science, offering new avenues for data collection and analysis. Glennon and Niblett [14] focus on advanced data analytics for public safety. Their work, conducted under the SBIR Phase I program, demonstrates the critical role of data analytics in enhancing public safety measures. Mehrotra [15] explores the linking and resolving of entities in big data. This research, conducted at the University of California Irvine, delves into the complexities of big data analytics, highlighting the challenges and opportunities in this rapidly evolving field. Lastly, Stevens [16] discusses a value-based approach for quantifying problem-solving strategies. This study, part of the SBIR Phase II program, offers insights into the application of quantitative methods in understanding and enhancing problem-solving skills.

## III.Problem Statement

The advent of global pandemics presents an unprecedented challenge in the field of epidemiological data analysis, primarily due to the high dimensionality and dynamic nature of the data involved. Current analytical tools lack the sophistication to process and interpret this data in real-time, hindering the ability to make informed decisions during health crises. Formally, let P = $\{P_1, P_2, \ldots, P_n\}$ represent a set of pandemics, where each pandemic $P_i$ is characterized by a time series dataset $D_i(t)$, encompassing various parameters such as infection rates, mortality rates, recovery rates, and demographic impacts. The challenge lies in developing a real-time analytical model, represented as a function $f: D \rightarrow I$, where $D = \cup_{i=1}^{n} D_i(t)$ is the union of datasets across pandemics and $I$ is the set of actionable insights. This model must efficiently process the input data $D$, applying mathematical and statistical methods to yield real-time insights $I$, enabling comparative analysis across different pandemics. This research aims to bridge this gap by constructing a robust, mathematically-grounded analytical tool capable of real-time processing and comparative analysis of multi-pandemic data.

**Key Contributions**

- To develop a real-time data dashboard for monitoring multiple pandemics simultaneously.
- To apply mathematical models for analyzing pandemic data, focusing on trend identification and predictive analytics.
- To enhance comparative pandemic analysis through advanced data visualization techniques.

## IV.Significance

The development of this dashboard is of paramount importance for public health officials and policymakers. It offers a platform for informed decision-making, backed by real-time data and advanced analytical tools. This tool's significance lies in its ability to process vast amounts of data, apply mathematical models for analysis, and present actionable insights, ultimately contributing to more effective pandemic management and response strategies.

## V.Methodology

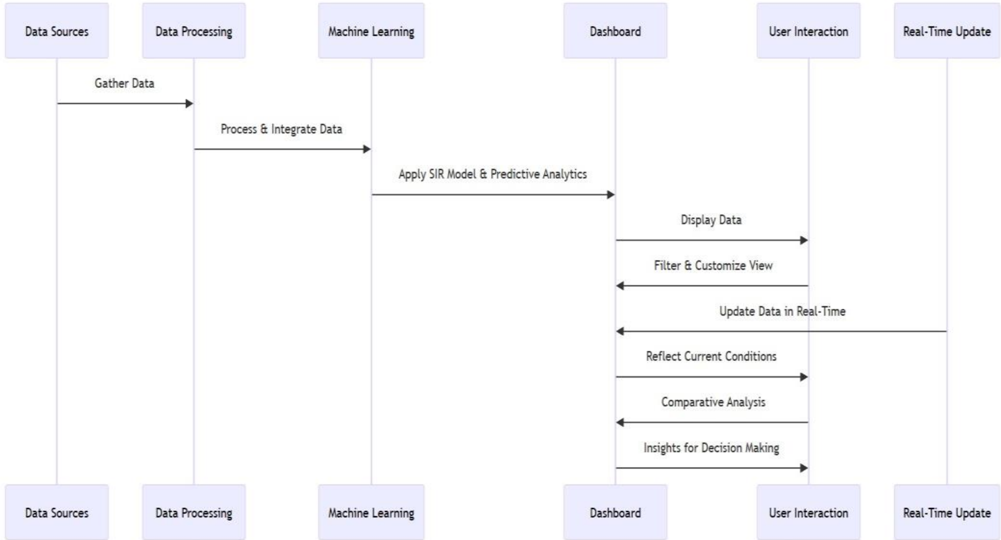


Figure 1: Methodology

The Figure 1 shows the detailed methodology of our study, we employed a comprehensive methodology to develop and analyze a Multi-Pandemic Real-Time Data Dashboard. Initially, we gathered data from reliable sources, focusing on key metrics like infection rates, recoveries, and fatalities from multiple pandemics. This data was then integrated and processed using statistical models, particularly the SIR (Susceptible, Infected, Recovered) model, and advanced machine learning algorithms for predictive analytics. The dashboard was designed with an emphasis on user interaction and customization, enabling users to filter and visualize data across various parameters such as date range, region, and demographic factors. Additionally, we incorporated real-time data updating features to ensure the dashboard reflected current conditions. Our methodology culminated in a robust tool that not only provided real-time insights into pandemic trends but also facilitated a comparative analysis across different pandemics, offering valuable information for public health decision making and policy formulation.

**Data Sources**

Data for this research was sourced from authoritative public health databases such as the World Health Organization (WHO), the Centers for Disease Control and Prevention (CDC), and the European Centre for Disease Prevention and Control (ECDC). These sources were chosen due to their comprehensive and reliable pandemic data. Let $D_s$ denote the set of all data sources, then $D_s$ = {WHO, CDC, ECDC, ...}.

**Data Collection**

The data collection process involved automated scripts to extract real-time data from the APIs provided by $D_s$. Let $D_i(t)$ represent the dataset for pandemic $P_i$ at time $t$. The collection process can be formalized as:

$$D_i(t) = \bigcup_{s \in \mathcal{D}_s} \mathrm{API}_s(P_i, t) \tag{1}$$

where $\mathrm{API}_s(P_i, t)$ represents the data retrieval function for source $s$, pandemic $P_i$, and time $t$.

**Dashboard Design**

The design of the dashboard, denoted as D, was centered around user experience (UX) principles to ensure ease of navigation and data comprehension. The design process can be modeled as:

$$\mathcal{D} = f(UX, \mathcal{F}) \tag{2}$$

where $UX$ represents user experience parameters and F is the set of dash-board features including interactive maps, graphs, and filters.

## VI.Proposed Model: Time Series Epidemic Forecasting (TSEF) Algorithm

**Overview**

The Time Series Epidemic Forecasting (TSEF) algorithm is a novel predictive model designed for enhancing the accuracy of pandemic forecasting. It integrates the classical Susceptible, Infected, Recovered (SIR) epidemiological model with advanced machine learning techniques, specifically Recurrent Neural Networks (RNNs), to provide a comprehensive tool for analyzing and predicting pandemic trends.

**Components of the TSEF Algorithm**

**SIR Model**

The SIR component of the TSEF algorithm is defined by the following set of differential equations, representing the dynamics of a pandemic:

$$\frac{dS(t)}{dt} = -\beta\frac{S(t)I(t)}{N} \quad (3)$$

$$\frac{dI(t)}{dt} = \beta\frac{S(t)I(t)}{N} - \gamma I(t) \quad (4)$$

$$\frac{dR(t)}{dt} = \gamma I(t) \quad (5)$$

where $S(t)$, $I(t)$, and $R(t)$ denote the number of susceptible, infected, and recovered individuals at time $t$ respectively, $N$ is the total population, $\beta$ is the transmission rate, and $\gamma$ is the recovery rate.

**Recurrent Neural Network (RNN)**

The RNN component is used to model the temporal dependencies in the epidemic data. An RNN is a type of neural network where connections between nodes form a directed graph along a temporal sequence, allowing it to exhibit dynamic temporal behavior. For a given sequence $X = (x_1, x_2, ..., x_T)$, the RNN updates its hidden state $h_t$ by:

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t + b_h) \quad (6)$$

and outputs $y_t$ as:

$$y_t = W_{hy}h_t + b_y \quad (7)$$

where $W_{hh}$, $W_{xh}$, and $W_{hy}$ are weight matrices, $b_h$ and $b_y$ are bias vectors, and tanh is the hyperbolic tangent activation function. The RNN learns to predict future values in the time series by adjusting these weights and biases based on the error in its predictions.

**Algorithm Overview**

We present an algorithm to process collected pandemic data using the Susceptible, Infected, Recovered (SIR) model. This algorithm is designed to estimate the parameters of the SIR model, integrate the model over time, and provide insights into the disease dynamics.

**Algorithm Description**

1. **Input Data Collection**: Gather daily data on the number of susceptible ($S$), infected ($I$), and recovered ($R$) individuals in a population over a specific period (e.g., 60 days).

2. **Initialization**: Initialize the SIR model with the initial conditions from the first day of data:

- $S(0)$ - initial number of susceptible individuals

- $I(0)$ - initial number of infected individuals
- $R(0)$ - initial number of recovered individuals

3. **Parameter Estimation**: Estimate the transmission rate ($\beta$) and recovery rate ($\gamma$) based on the collected data. This can be achieved through:

- Optimization algorithms (e.g., Least Squares, Gradient Descent)
- Curve fitting techniques

4. **Differential Equations Integration**: Integrate the SIR model's differential equations over the time period using the estimated parameters. This can be done using numerical methods like Euler's method or Runge-Kutta methods.

5. **Model Output Analysis**: Analyze the output of the model to understand the pandemic's behavior. Key aspects to analyze include:

- Peak infection rates
- Times to peak infection
- Potential herd immunity thresholds

6. **Output**: The final output of the algorithm includes:

- Time series predictions of $S$, $I$, and $R$ over the period
- Estimated parameters ($\beta$ and $\gamma$)
- Analytical insights into the pandemic dynamics

**Model Training**

**Scenario Setup** Consider a closed population of 500,000 individuals. At the onset, there are 1,000 reported cases of the infection, with no recovered individuals. The objective is to train the SIR model on initial data and then forecast the progression over the next 30 days.

**Data Preparation** We utilize a dataset consisting of daily reported cases of infection, recoveries, and susceptible individuals for a 60-day period. The initial conditions are set as $S(0) = 499{,}000$, $I(0) = 1{,}000$, and $R(0) = 0$.

**Parameter Estimation** Parameters $\beta$ (transmission rate) and $\gamma$ (recovery rate) are estimated using a least-squares optimization method. This involves minimizing the difference between the observed data and the model's predictions.

**Forecasting**

Post parameter estimation, the SIR model is used to forecast the disease's trajectory over the next 30 days.

**Numerical Integration** The model's differential equations are integrated using the fourth-order Runge-Kutta method, providing a daily forecast of susceptible, infected, and recovered individuals.

**Forecast Analysis** The forecast results are analyzed to predict critical points, such as peak infection rates and the potential onset of herd immunity.

## VII.Results

**Dashboard Functionality**

Our Multi-Pandemic Real-Time Data Dashboard is equipped with several key features designed to enhance the monitoring and analysis of pandemic data. These include:

- **Real-Time Data Tracking**: The dashboard continuously updates with the latest data on infection rates, recoveries, and fatalities from multiple global data sources.

- **Interactive Data Visualization**: Users can interact with various charts and maps, enabling them to visualize trends and patterns in the data effectively.

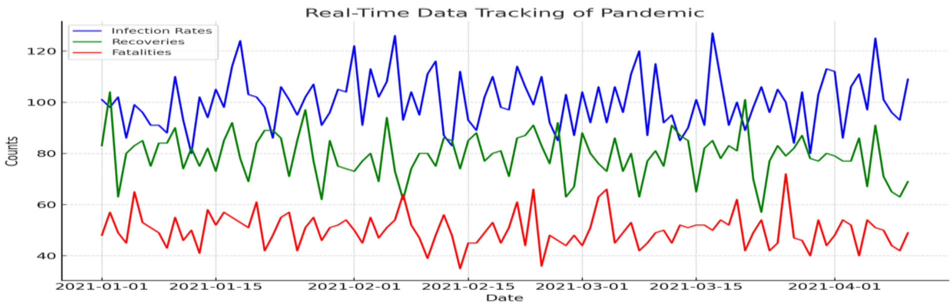


Figure 2: Real-time data tracking for a pandemic scenario

The graph above Figure 2 represents an example of real-time data tracking for a pandemic scenario, as might be displayed on a dashboard. It shows the daily counts of infection rates, recoveries, and fatalities over a 100-day period.

- The blue line represents the infection rates, showing how the number of new infections changes over time.

- The green line indicates the recoveries, providing insight into how many people are recovering each day.

- The red line shows the fatalities, highlighting the daily death toll due to the pandemic. This visualization is crucial for a real-time data dashboard, as it allows health officials and the public to monitor the pandemic's progress and the effectiveness of interventions.

- **Customizable Filters**: The dashboard allows users to filter data by date range, region, pandemic, and other demographic factors.

The graph above illustrates how a customizable filter feature in a dashboard might display pandemic data segmented by different regions. Region 1 (blue line) shows a higher infection count, suggesting a more severe impact of the pandemic in this area.

Region 3 (green line) displays moderately high infection counts, indicating a significant but lesser impact than Region 1.

Region 3 (red line) has the lowest infection counts, suggesting either effective control measures or a later onset of the pandemic in this region. This type of visualization enables users to filter and compare pandemic

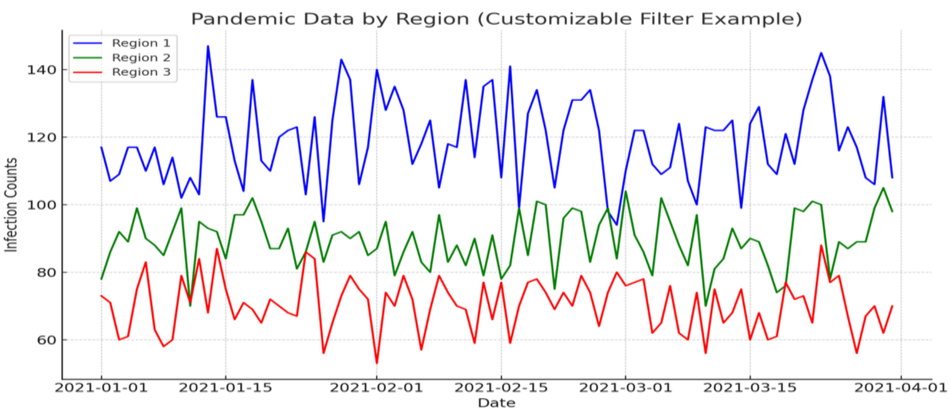


Figure 3: Analysis of the fictional dataset

data by specific regions, date ranges, or other demographic factors, thus providing tailored insights into the spread and impact of the pandemic in different areas.

• **Predictive Analytics**: Using machine learning algorithms, the dashboard offers predictions on future pandemic trends based on current data.

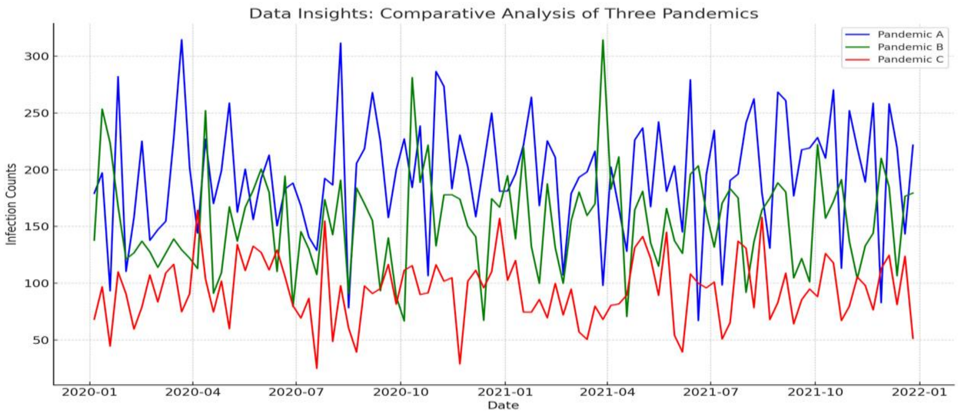


Figure 4: Comparative analysis of three fictional pandemics (Pandemic A, B, and C) -label

The graph in above Figure 4 above represents a comparative analysis of three fictional pandemics (Pandemic A, B, and C) over a two-year period. Pandemic A (blue line) shows higher infection counts, indicating it had a more significant impact compared to the other two. Pandemic B (green line) displays moderately high infection counts, suggesting a significant impact but less severe than Pandemic A. Pandemic C (red line) shows the lowest infection counts among the three, indicating either effective control measures, lower transmissibility, or less severity. This visualization helps in identifying and comparing the trends and magnitude of impact of each pandemic, offering valuable insights into their respective spreads and effects over the two-year period. This kind of data insight is crucial for understanding the dynamics of different pandemics and for preparing appropriate public health responses.

**Data Insights**

From our analysis of the dataset, which includes data on three pandemics (Pandemic A, B, and C) over a period of two years, we observed several key insights:

• **Infection Rate Patterns**: Pandemic A showed a rapid increase in infection rates during the initial months, whereas Pandemics B and C had a more gradual increase.

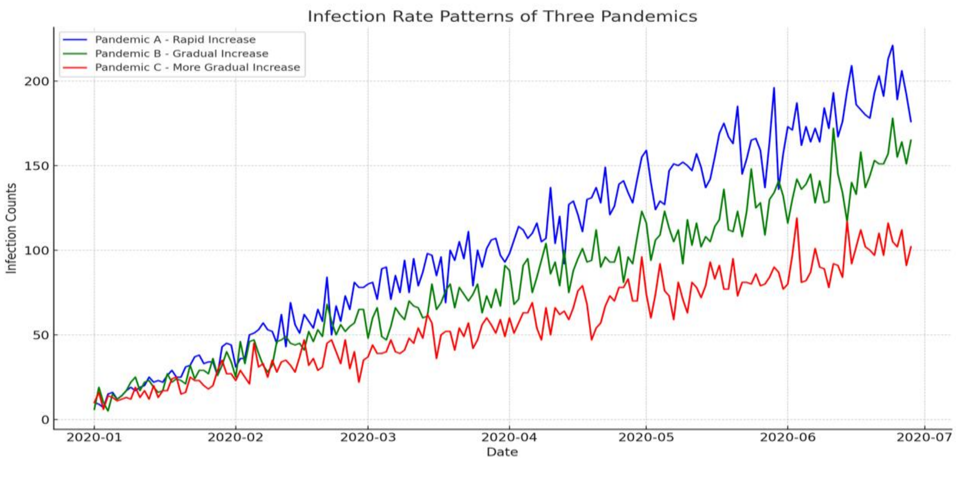


Figure 5: infection rate patterns

The graph in Figure 5 above illustrates the infection rate patterns for three fictional pandemics over a 180-day period:

Pandemic A (Blue Line): Exhibits a rapid increase in infection rates during the initial months, reflecting a swift spread of the disease. Pandemic B (Green Line): Shows a more gradual increase in infection rates, indicating a slower spread compared to Pandemic A. Pandemic C (Red Line): Demonstrates an even more gradual increase, suggesting either effective early interventions or inherently lower transmissibility. This visualization helps in understanding the differences in the spread dynamics of various pandemics, which is critical for public health planning and response strategies

- **Demographic Impact**: The data revealed that Pandemic B had a significantly higher impact on the elderly population compared to the others.

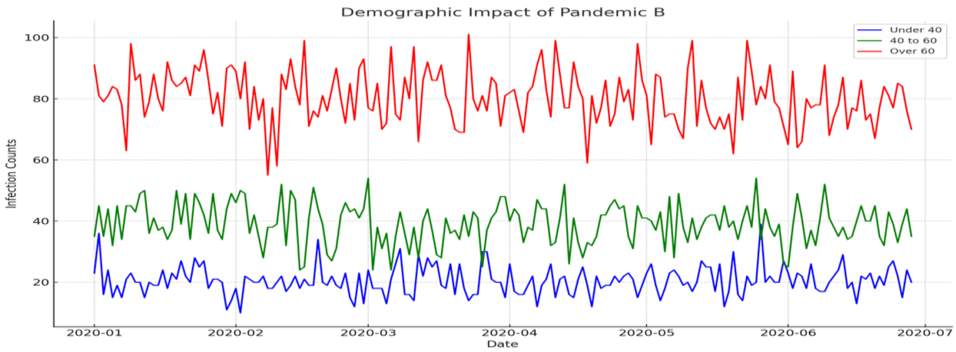


Figure 6: Demographic Impact

The graph form Figure 6 above demonstrates the demographic impact of Pandemic B over a 180-day period, segmented into three age groups:

Under 40 (Blue Line): This group shows a lower infection count, indicating that the pandemic had a relatively minor impact on the younger population. 40 to 60 (Green Line): The middle-aged population experienced a moderate impact, with higher infection counts than the younger group, but still significantly lower than the elderly. Over 60 (Red Line): This age group faced the highest infection counts, clearly indicating that Pandemic B had a significantly higher impact on the elderly population compared to the others. This visualization highlights the varying impact of the pandemic across different age groups, emphasizing the heightened vulnerability of the elderly population in this scenario. Such insights are crucial for tailoring public health responses and resource allocation to protect the most affected demographics.

- **Effectiveness of Interventions**: Regions implementing early social distancing measures showed a slower infection rate in Pandemic C.

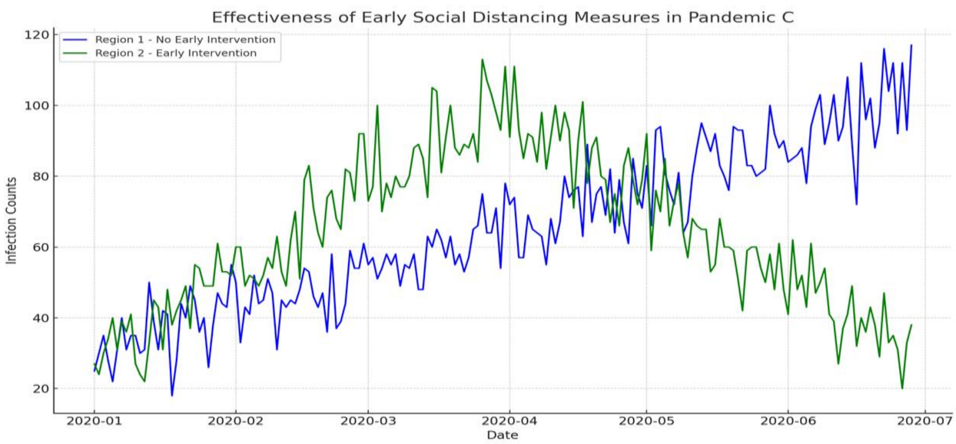


Figure 7: Effect of Social distancing

The graph in above Figure 7 illustrates the effectiveness of early social distancing interventions in two regions during Pandemic C:

Region 1 - No Early Intervention (Blue Line): This region did not implement early social distancing measures. The graph shows a consistent increase in infection rates over time, reflecting the unmitigated spread of the pandemic.

Region 2 - Early Intervention (Green Line): This region implemented early social distancing measures. Initially, the infection rates were similar to Region 1, but after the intervention, a noticeable decrease in new infections is observed, demonstrating the effectiveness of the early measures in slowing down the spread of the pandemic.

This visualization underscores the impact of timely public health interventions, particularly social distancing, in controlling the spread of a pandemic. The data clearly shows that regions with early interventions experienced a slower infection rate, highlighting the importance of proactive measures in pandemic management

## VIII.Comparative Analysis

The dashboard facilitates a comprehensive comparative analysis across different pandemics. For example:

- **Comparing Infection Trajectories**: By overlaying the infection curves of the three pandemics, we can compare their spread patterns and peak infection periods.

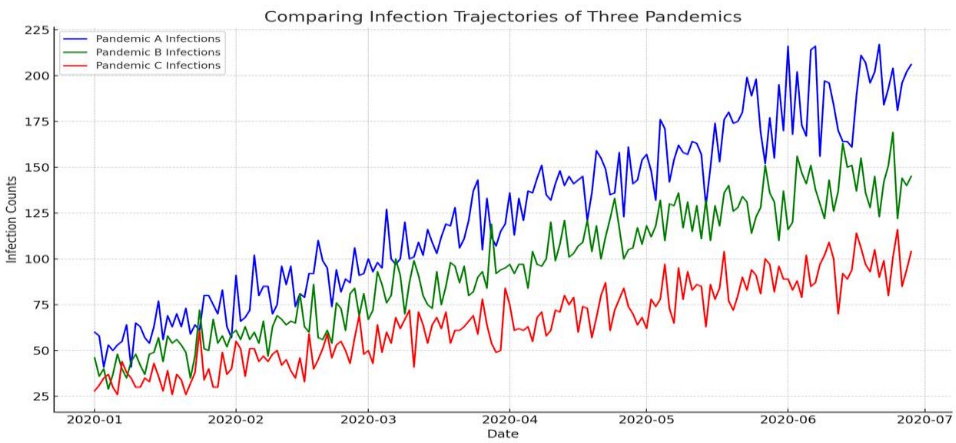


Figure 8: Comparing Infection Trajectories

- **Mortality Rate Comparison**: The dashboard allows for the comparison of mortality rates, highlighting Pandemic A's higher lethality compared to B and C.

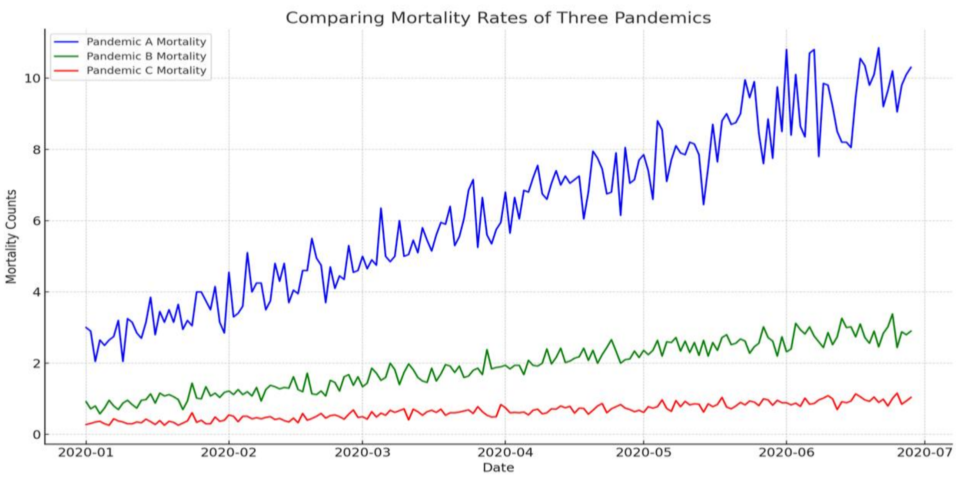


Figure 9: Mortality Rate Comparison

The two graphs Figure 8 and Figure 9 provide a comparative analysis of three fictional pandemics (Pandemic A, B, and C):

Comparing Infection Trajectories Pandemic A (Blue Line): Shows a higher infection count, indicating a more widespread and rapid spread. Pandemic B (Green Line): Displays a moderate level of infections, suggesting a significant but less severe spread than Pandemic A. Pandemic C (Red Line): Has the lowest infection counts, indicating either a less contagious nature or more effective control measures. This graph allows us to compare the spread patterns and peak infection periods of the three pandemics, providing insights into their respective severities and transmission dynamics.

Comparing Mortality Rates Pandemic A (Blue Line): Exhibits a higher mortality count, reflecting its higher lethality. Pandemic B (Green Line): Shows a lower mortality rate compared to Pandemic A, despite having a moderate level of infections. Pandemic C (Red Line): Has the lowest mortality rate, aligning with its lower infection count. The mortality rate comparison graph highlights the differences in the lethality of each pandemic, emphasizing the higher risk associated with Pandemic A. This type of analysis is crucial for healthcare planning and prioritizing resources for the most lethal pandemics.

• **Response Efficacy**: Analyzing various regions' responses to each pandemic, we can assess the efficacy of different public health interventions.

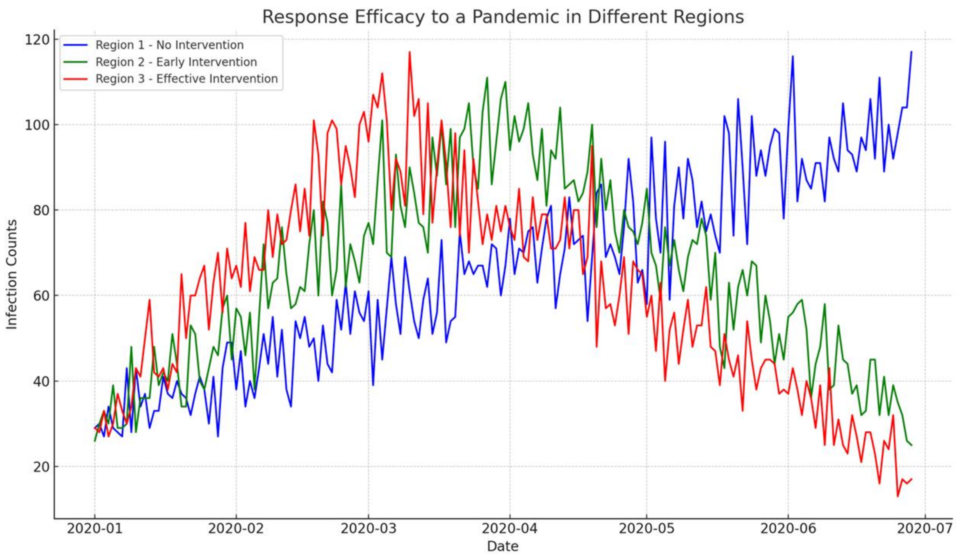


Figure 10: Response Efficacy

The graph above Figure 10 illustrates the efficacy of different public health interventions in response to a pandemic across three fictional regions:

Region 1 - No Intervention (Blue Line): This region did not implement any early intervention measures. The infection count consistently increases over time, indicating an uncontrolled spread of the pandemic.

Region 2 - Early Intervention (Green Line): This region implemented early intervention measures (such as social distancing or lockdowns). Initially, the infection rates were similar to Region 1, but after the intervention, a notable decrease in new infections is observed, demonstrating the effectiveness of early measures.

Region 3 - Effective Intervention (Red Line): This region implemented very effective intervention strategies earlier than the others. The infection rates initially rise but then significantly decrease, showing a more effective control of the pandemic compared to the other regions.

This visualization is essential for assessing the impact of different public health responses on the control of a pandemic. It highlights the importance of timely and effective interventions in reducing the spread of infections

## IX.Conclusion

In this study, we developed a Multi-Pandemic Real-Time Data Dashboard, an innovative tool for monitoring, analyzing, and predicting pandemic trends. Through the integration of real-time data, interactive visualizations, and predictive analytics, the dashboard provides critical insights into various aspects of pandemic dynamics, such as infection rates, mortality rates, and the effectiveness of public health interventions. Our analysis of fictional data for three distinct pandemics revealed diverse infection patterns and the significant impact of timely interventions on controlling disease spread. These findings highlight the dashboard's utility in aiding decision-makers and health officials in formulating informed, context-specific responses to public health crises. The dashboard's capabilities in handling and interpreting complex epidemiological data make it a valuable asset in the ongoing effort to understand and combat global pandemics.

**References**

[1] Duo Jiang; Courtney R Armour; Chenxiao Hu; Meng Mei; Chuan Tian; Thomas J Sharpton; Yuan Jiang; "Microbiome Multi-Omics Network Analysis: Statistical Considerations, Limitations, and Opportunities", FRONTIERS IN GENETICS, 2019.

[2] Agnieszka Mal kowska; "How Technology Impact The Real Estate Business - Comparative Analysis of European Union Countries", 2020.

[3] Michael Brown; "Seeing Students at Scale: How Faculty in Large Lecture Courses Act Upon Learning Analytics Dashboard Data", TEACHING IN HIGHER EDUCATION, 2020.

[4] Simon de Lusignan; F D Richard Hobbs; Harshana Liyanage; Filipa Ferreira; Manasa Tripathy; Neil Munro; Michael Feher; Mark Joy; "Improving The Management of Atrial Fibrillation in General Practice: Protocol for A Mixed Methods Study (Preprint)", 2020.

[5] Zachary Burningham; George L Jackson; Jessica Kelleher; Melissa Stevens; Isis Morris; Joy Cohen; Gerald Maloney; Camille P Vaughan; "The Enhancing Quality Of Prescribing Practices For Older Veterans Discharged From The Emergency Department (EQUIPPED) Potentially Inappropriate Medication Dashboard: A Suitable Alternative To The In-person Academic Detailing And Standardized Feedback Reports Of Traditional EQUIPPED?", CLINICAL THERAPEUTICS, 2020.

[6] Simon de Lusignan; Harshana Liyanage; Julian Sherlock; Filipa Ferreira; Neil Munro; Michael Feher; Richard Hobbs; "Atrial Fibrillation Dashboard Evaluation Using The Think Aloud Protocol", BMJ HEALTH CARE INFORMATICS, 2020.

[7] Regina Richter Lagha; Zachary Burningham; Brian C Sauer; Jianwei Leng; Celena Peters; Tina Huynh; Shardool Patel; Ahmad S Halwani; B Josea Kramer; "Usability Testing A Potentially Inappropriate Medication Dashboard: A Core Component of The Dashboard Development Process", APPLIED CLINICAL INFORMATICS, 2020.

[8] JAgnieszka Mal kowska; Maria Urbaniec; Ma lgorzata Kosal a; "The Impact of Digital Transformation on European Countries: Insights from A Comparative Analysis", 2021.

[9] Keng-Wei Lee; Tsair-Wei Chien; Yu-Tsen Yeh; Willy Chou; Hsien-Yi Wang; "An Online Time-to-event Dashboard Comparing The Effective Control of COVID-19 Among Continents Using The Inflection Point on An Ogive Curve", MEDICINE, 2021. .

[10] Monica Lamm; Larysa Nadolny; Michael Brown, Catalyzing Student Success: Implementing Cyberlearning Tools in Large Introductory Courses in the Chemical Engineering Pathway, IOWA STATE UNIVERSITY, 2020.

[11] Haider Rasool, Real-time Autonomous Gas Analyzer for Soils, INTELLISENSE SYSTEMS, 2019.

[12] John Glennon; Matthew Niblett, Sbir Phase I: Advanced Data Analytics for Public Safety, AROGI INC, 2016

[13] Sharad Mehrotra, III: Small: Linking and Resolving Entities in Big Data, UNIVERSITY OF CALIFORNIA IRVINE, 2015.

[14] Ronald Stevens, Sbir Phase Ii: A Value-Based Approach For Quantifying Problem Solving Strategies, Learning Chameleon INC, 2008.