Matrik: Jurnal Manajemen, Teknik Informatika, dan Rekayasa Komputer
Vol. 23, No. 3, July 2024, pp. 581∼590
ISSN: 2476-9843, accredited by Kemenristekdikti, Decree No: 200/M/KPT/2020
DOI: 10.30812/matrik.v23i3.4000

New Method for Identification and Response to Infectious Disease Patterns Based on Comprehensive Health Service Data

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Article Info

Article history:

Received April 23, 2024
Revised May 30, 2024
Accepted June 05, 2024

Keywords:

Comprehensive Health Data
Disease Patterns
Health Service Data
Infectious Diseases

ABSTRACT

Infectious diseases continue to pose a major threat to global public health and require early detection and effective response strategies. Despite advances in information technology and data analysis, the full potential of health data in identifying disease patterns and trends remains underutilized. **This study aimed to** propose a comprehensive new mathematical model new method that utilizes health data to identify infectious disease patterns and trends by exploring the potential of data-driven care approaches in addressing public health challenges associated with infectious diseases. **The research method**s used were exploratory data collection and analytical model development. **The research results obtained** mathematical models and algorithms that consider data of period, time, patterns, and trends of dangerous diseases, statistical analysis, and recommendations. Data visualization and in-depth analysis were conducted in the research to improve the ability to respond to infectious disease threats, provide better decision-making solutions in improving outbreak response, and improve preparedness in addressing public health challenges. **This research contribute**s to health practitioners and decision-makers.

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How to Cite:
D. Vinsensia, S. Amri, J. Sihotang, and H. Sihotang, ”New Method for Identification and Response to Infectious Disease Patterns Based on Comprehensive Health Service Data”, *MATRIK: Jurnal Manajemen, Teknik Informatika, dan Rekayasa Komputer*, Vol. 23, No. 3, pp. 581-590, July, 2024.

1. INTRODUCTION

Infectious diseases pose a serious threat to public health worldwide. Early detection, understanding patterns, and disease trends are key to effective control efforts [1–3]. In the digital era and with advancements in information technology, data-driven care approaches promise potentially effective solutions in identifying and combating infectious diseases more effectively [4–6]. This research aims to explore the potential of this approach in addressing public health challenges related to infectious diseases [7, 8]. Despite advancements in information technology and data analysis in recent decades, the utilization of health data to identify disease patterns and trends remains suboptimal [9, 10]. Challenges such as data heterogeneity, infrastructure limitations, and lack of system integration hinder effective analysis [11, 12]. Therefore, this research aims to gain a deeper understanding of how data-driven care approaches can be used to enhance understanding and response to infectious diseases [13, 14]. The main issue faced is the underutilization of the potential of health data in infectious disease control [15, 16]. Challenges to inconsistent data collection, data integration from various sources, and accurate data analysis for identifying patterns and trends hinder early outbreak detection, predictive modeling, and the development of responsive monitoring systems [16, 13].

Previous research conducted by A. N. Desai et al. in 2021, titled Developing a Data-driven Approach in Order to Improve the Safety and Quality of Patient Care [17], has highlighted the importance of which is titled data-driven care approaches in the context of public health. These studies indicate that careful data analysis can provide valuable insights into early detection of infectious diseases and better decision-making in health management. The theories for supporting this research include concepts in epidemiology, statistical analysis, information technology, and data management. In addition to the above research, Wang et al. 2022 also researched Combining Theory and Data-Driven Approaches for Epidemic Forecasts in Knowledge Guided Machine Learning. Wang et al., in their research, developed appropriate mathematical modeling formulations to leverage data-driven care approaches, both for behavior change and addressing public health challenges related to the spread of infectious diseases.

Based on the description of previous research above, this research solves the problem of handling data analysis on a large scale. There is a gap in proper management and analysis to obtain meaningful information, especially requiring fast processing and capturing the dynamic nature of disease transmission, thus limiting predictions accuracy and consistency. The plan for completing the research includes comprehensive data collection, developing appropriate analysis models, and implementing adequate information technology to support health data management, which has been explained by previous researchers [18]. However, in solving the problem of handling data analysis on a large scale, **there is a gap in** proper management, and analysis is needed to obtain meaningful information, especially requiring fast processing and fully capturing the dynamic nature of disease transmission, thereby limiting the accuracy and consistency of predictions. Thus, modeling is needed to mitigate risk by predicting distribution patterns or measuring the impact of various intervention strategies on the dynamics of infectious disease transmission. Through a multidisciplinary and collaborative approach, it is hoped that this research can yield a better understanding of leveraging data-driven care approaches to identify infectious disease patterns and trends more effectively [19]. Existing research has not addressed the problem of big and uncertain data. Therefore, the main objective of this research is to solve these problems.

The difference between this research and the previous one lies in the proposal to develop new methods in data-driven care approaches, addressing public health challenges related to infectious diseases by visualizing data. Through in-depth analysis, this research is expected to provide valuable insights for healthcare practitioners and decision-makers in infectious disease control. The research aims to improve the health systems ability to respond to infectious disease threats, leading to better decision-making, enhanced outbreak responses, and improved readiness to address public health challenges. The main contribution of this research is a new method in the form of mathematical formulations to solve the above problems, with expected benefits of this research including improving the health systems ability to address infectious disease threats through more effective utilization of health data. A better understanding of disease patterns and trends is hoped to enhance responses to outbreaks, make better decisions in health management, and improve readiness to face public health challenges.

2. RESEARCH METHOD

This section introduces the concept of a new model or method for detecting and determining the trend and pattern of the spread of infectious diseases. The research method used in this study is experimental research, proposing a new method to detect and determine the trend and pattern of the spread of infectious diseases. The data used is testing data by providing the assumptions for six months of X-virus infection. Utilization of Health Data: Previous studies have highlighted the underutilization of health data in infectious disease control. Challenges such as data heterogeneity, infrastructure limitations, and integration issues have been identified as barriers to effective data analysis. This research has four stages, starting from Literature Study on Data-driven approach, Concept of Optimization, Concept of Modeling, Concept of Prediction, models for analyzing disease patterns and trends, modeling of microbial infections, Data-driven research meets theory-driven research, Analysis of big data in health sector, Data-driven methods.

The problem is then identified and formulated, and the research objectives are determined. The second stage involves analyzing the need to formulate a new method, which consists of several stages: defining the parameters and variables necessary for building a new formulation, determining the formulation methods such as regression analysis, time series analysis, or machine learning algorithms to be used, formulating a new method named the HD-IDPIR Method following the objective function, and defining and analyzing input and output data. After completing the second stage, enter the third stage, namely creating an algorithm according to the process flow of the formulated HD-IDPIR Method, testing the formulation of the method using the Looker Studio Overview application, of course, with six months of infectious disease data testing data. If it has a feasible solution, then proceed to the stage of making conclusions. If not, then it will return to the second stage. This is done repetitively in the research method with instruments until the right solution is found. For details, see Figure 1.

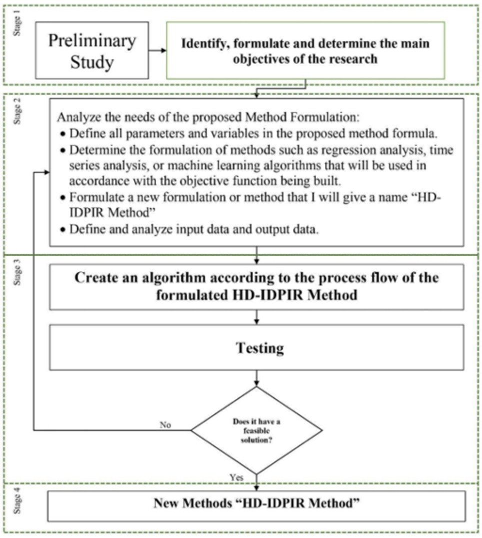

Figure 1. Flow of Research

Significance of Data-Driven Approaches: Research underscores the importance of data-driven approaches in early disease detection and response. By harnessing the power of data analytics, healthcare practitioners can gain valuable insights into disease patterns and trends, facilitating more informed decision-making [20–22]. Theoretical foundations and theoretical frameworks from epidemiology, statistical analysis, information technology, and data management provide the basis for formulating effective research methodologies [23–26]. Concepts such as epidemic modeling, data mining, and machine learning are instrumental in analyzing health data and identifying actionable insights [27].

Methodological Approaches: Studies have employed diverse methodologies to leverage health data for infectious disease control [28]. Comprehensive data collection strategies, developing sophisticated analysis models, and implementing advanced information technology systems are commonly utilized to enhance data-driven decision-making [29]. Collaborative Efforts: Collaboration across disciplines is essential for addressing the complex challenges associated with infectious diseases [30, 31]. Multidisciplinary research teams combine expertise from various fields to develop holistic solutions and improve public health outcomes [32–34].

2.1. Basic Mathematical Formulation

To solve the problem of underutilization of health data in infectious disease control, a mathematical formulation can be developed to guide data analysis and decision-making processes. One approach involves using statistical models to analyze disease patterns and trends: Let D represent the set of infectious disease data, including variables such as incidence rates, demographic information, and geographic location. Let M denote the statistical model used for data analysis, which may include regression analysis, time series analysis, or machine learning algorithms. The goal is to maximize the utility of health data D by fitting the statistical model M to identify patterns and trends in infectious diseases, as shown eq. (1) as follows:

$$\begin{gathered} max_M U(D, M) \\ Constraints : C_1, C_2, C_3 \ldots C_n \end{gathered} \tag{1}$$

Where $U(D, M)$ represents the utility function, quantifying the effectiveness of the statistical model M in extracting valuable insights from the health data D.

2.2. Proposed model Comprehensive Healthcare Data-Driven Infectious Disease Pattern Identification and Response (HD-IDPIR) Method

A focus on key components such as data integration, pattern recognition, and decision-making are essential to develop a more specific mathematical formulation for addressing the research problem of underutilization of health data in infectious disease control. Let D_i represents the dataset associated with infectious disease i, comprising various data types such as incidence rates, demographic information, and geographic factors. Let T denotes the time period over which the data is collected and analyzed. Let P represents the set of potential disease patterns and trends that can be identified from the data. Let M denotes the mathematical model or algorithm used for data analysis, incorporating techniques such as machine learning, time series analysis, or spatial analysis. Let R denotes the set of recommendations or decisions generated based on the analysis of the health data. The following is the formulation of the objective function as in equation (2). Where $U(D_1, D_2, D_3 \ldots D_n T, P, M, R)$ represents the utility function, quantifying the effectiveness of the mathematical model M in extracting valuable insights from the health data $D_1, D_2, D_3 \ldots D_n$ over time T, identifying relevant patterns P, and generating actionable recommendations R.

$$\begin{gathered} max_{M,R}\, U\left(D_1, D_2, D_3 \ldots D_n T, P, M, R\right) \\ constraints: C_1, C_2, C_3 \ldots C_n \end{gathered} \tag{2}$$

2.3. Numerical example

Let us create a simplified numerical example to demonstrate how the proposed mathematical formulation (HD-IDPIR Method) could be applied in a research scenario focused on infectious disease control. Scenario: Consider a research project aiming to analyze health data to identify patterns and trends in spreading a fictitious infectious disease called "X-virus" in a small community over six months. Data: The dataset D consists of the following variables for each month: (a) Incidence rates of X-virus infections, (b) Demographic information (e.g., age, gender) of infected individuals, (c). Geographic location of reported cases period: T =1,2,3,4,5,6 (representing six months) Potential Disease Patterns: P= $Seasonalvariations, Clusteroutbreaks, Demographicpredispositions$ Mathematical Model: For simplicity, let us consider using a linear regression model to analyze the data and identify patterns. Recommendations: R could include strategies for targeted vaccination campaigns, public awareness campaigns, or resource allocation based on the identified patterns and trends. Objective Function: The objective function U quantifies the utility of the analysis and recommendations in mitigating the spread of X-virus and minimizing its impact on the community. Now, let us create some sample data for illustration purposes, as shown in Table 1.

Table 1. Sample data

Month	Incidence Rate	Age Distribution	Geographic Location
1	10	Children (30%)	Urban
2	15	Adults (50%)	Rural
3	20	Elderly (20%)	Suburban
4	25	Adults (60%)	Urban
5	30	Children (40%)	Rural
6	35	Adults (70%)	Suburban

3. RESULT AND ANALYSIS

The findings of this research are in the form of a proposed new method in the form of a mathematical formulation proposed in section 2.2, named the HD-IDPIR Method. After testing the method with a numerical example using the last six months of data on the spread of virus X, results indicate that a higher U value corresponds to a higher incidence rate and greater potential urgency for intervention. Considering Figure 2: Each asterisk (*) represents the incidence rate in a given month, with the x-axis representing the month and the y-axis representing the incidence rate.

A simplified approach is applied to solve the given numerical example using the new mathematical formulation (HD-IDPIR Method), focusing on identifying patterns and trends in the spread of the X-virus and generating recommendations based on the analysis. Objective Function: Lets define a simple objective function U that quantifies the utility of the analysis and recommendations, as shown in equation (3).

$$U = \sum_{i=1}^{6} (IncidenceRate_i \times Weight_i) \tag{3}$$

Where: $IncidenceRate_i$ represents the incidence rate of X-virus infections in month i. $Weight_i$ represents the weight assigned to each month based on its importance in the analysis (e.g., recent months may be given higher weights to prioritize current trends). Constraints are introduced to ensure the feasibility and relevance of the recommendations. For example, limitations on the total budget for intervention strategies could be included as constraints, ensuring equitable distribution of resources across demographic groups or geographic locations. Setting thresholds for acceptable incidence rates or rates of change. Solution Approach: Since this is a simplified example, complex optimization techniques will not be used. Instead, the objective function will be demonstrated to prioritize months with higher incidence rates for targeted interventions. Let us assign arbitrary weights to each month based on its importance Weight= 1,2,3,4,5,6. Now, the utility U will be calculated using the provided data.

$$U = (10 \times 1) + (15 \times 2) + (20 \times 3) + (25 \times 4) + (30 \times 5) + (35 \times 6)$$
$$U = 10 + 30 + 60 + 100 + 150 + 210$$
$$U = 560$$

In this simplified example, the utility U quantifies the overall impact of X-virus spread over the six months. Higher values of U indicate higher incidence rates and potentially greater urgency for intervention. Based on the calculated utility and any predefined constraints, recommendations can be generated to address the identified patterns and trends in X-virus spread, such as allocating resources for vaccination campaigns, public health education, or targeted interventions in areas with the highest incidence rates. While this approach provides a basic demonstration of using mathematical formulation to solve the problem, in practice, more sophisticated models and optimization techniques would be employed to account for complex factors and optimize decision-making in infectious disease control. Visualizing the given data and expressing it in a mathematical formulation, the incidence rate of infection of virus X over six months can be represented using a bar chart. Each bar will correspond to the incidence rate in a particular month, making comparisons and trend identification easy. Month 1 Jan:10, Month 2 (February):15, Month 3 (Mar):20, Month 4 (April):25, Month 5 (May):30, Month 6 (Jun):35. Figure 2 Data visualization using bar charts.

Figure 2. Visualization results of sample data

Each asterisk (*) represents the incidence rate for a specific month, with the x-axis representing the months and the y-axis representing the incidence rates. Now, let us incorporate this visualization into the mathematical formulation. The objective function U will be defined to quantify the overall impact of X-virus spread based on the incidence rates as shown in Equation (3.). Where: $IncidenceRate_i$ represents the incidence rate of X-virus infections in month i. $Weight_i$ represents the weight assigned to each month based on its importance in the analysis. For visualization purposes, equal weights can be assigned to each month: Weight=1,1,1,1,1,1, Now, let us calculate the utility U using the provided data:

$$U = \sum_{i=1}^{6} (IncidenceRate_i \times Weight_i) \tag{4}$$

$$U = (10 \times 1) + (15 \times 1) + (20 \times 1) + (25 \times 1) + (30 \times 1) + (35 \times 1)$$
$$U = 10 + 15 + 20 + 25 + 30 + 35$$
$$U = 135$$

In this formulation, the utility U quantifies the overall impact of X-virus spread over the six months. Higher values of U indicate higher incidence rates and potentially greater urgency for intervention. The following is an algorithm to analyze sample data of X virus incidence rate over six months and generate recommendations based on the analysis. Input: Incidence rates of X-virus infections for each month. Weight assigned to each month (optional). Calculate Utility Function: Initialize utility function U to 0. For each month i from 1 to 6: (Calculate the product of the incidence rate for month i and its corresponding weight (if applicable). Add the result to the utility function U.) Generate Recommendations: Based on the calculated utility function U: Identify months with higher incidence rates or significant rate increases. Determine areas or demographic groups with the highest incidence rates. Propose targeted interventions such as vaccination campaigns, public health education, or resource allocation in high-risk areas. Output: Utility function value U, indicating the overall impact of X-virus spreadrecommendations for infectious disease control strategies based on the analysis.

Figure 3 serves as a logical step of the proposed mathematical formulation, and the point is to provide an understanding of how the proposed mathematical formulation can run and can be executed if the formulation is converted into an intelligent system application, so Figure 2 is basic logic. Diverse multidimensional factors may contribute to the Incidence rates of X-virus infections for each month and the rate of disease spread, [35]. Examining and developing variables that account for the weight of the disease-spreading process can improve the effectiveness of applying predictive variables to understand the dynamics of infectious diseases. The proposed algorithm in Figure 2 provides a structured approach to analyze the sample data of X-virus incidence rates and generate recommendations for infectious disease control strategies based on the analysis. This studys results align with research [36] in handling data on a big scale. The proposed algorithm can be adapted and extended to handle more complex data and decision-making scenarios in real-world applications.

```
Function Analyze_X_Virus_Data(Incidence_Rates, Weights):
    Initialize utility_function = 0

    For i = 1 to 6:
        If Weights are provided:
            Calculate weighted_incidence_rate = Incidence_Rates[i] * Weights[i]
        Else:
            Set weighted_incidence_rate = Incidence_Rates[i]

        Add weighted_incidence_rate to utility_function

    Return utility_function

Function Generate_Recommendations(Incidence_Rates):
    For i = 1 to 6:
        If Incidence_Rates[i] is high or increasing:
            Identify high-risk areas or demographic groups

    Generate recommendations based on identified patterns and trends

Main:
    Incidence_Rates = {10, 15, 20, 25, 30, 35}
    Weights = {1, 1, 1, 1, 1, 1}  // Optional weights for months

    utility_function = Analyze_X_Virus_Data(Incidence_Rates, Weights)
    recommendations = Generate_Recommendations(Incidence_Rates)

    Display utility_function
    Display recommendations
```

Figure 3. Algorithmic Model of the Proposed Mathematical Formulation (HD-IDPIR Method)

4. CONCLUSION

This research has demonstrated the applicability of a data-driven approach in analyzing the incidence rate of X-virus infection over a six-month period and generating recommendations for infectious disease control strategies. Through the use of mathematical formulations and algorithmic analysis (the proposed method/HD-IDPIR Method), valuable insights have been gained into the patterns and trends of X-virus spread, assisting in the formulation of targeted interventions to reduce its impact on society. The analysis revealed that the incidence rate of X-virus infection showed an increasing trend over a six-month period, indicating an increasing public health concern. By prioritizing months with higher incidence rates and identifying high-risk areas or demographic groups, recommendations were made to address the observed patterns and trends effectively. These recommendations include implementing targeted vaccination campaigns, intensifying public health education efforts, and allocating resources to high-risk areas for early detection and containment of the spread of virus X. By utilizing the proposed model or method with a data-driven approach, public health authorities can make informed decisions and take proactive measures to protect public health and prevent infectious disease outbreaks. It is essential to acknowledge the limitations of this research, including the simplifications made in the analysis and the reliance on hypothetical data. Future studies could explore more sophisticated modeling techniques, incorporate additional data sources, and validate the effectiveness of recommended interventions through real-world implementation and evaluation. This research contributes to the growing body of knowledge on infectious disease control strategies, highlighting the importance of data-driven decision-making in safeguarding public health and ensuring the well-being of communities in the face of emerging health threats. Future research endeavors should continue to advance the integration of data-driven approaches into infectious disease control strategies, ultimately contributing to more effective public health responses and safeguarding community well-being.

5. ACKNOWLEDGEMENTS

Thanks to the Institute of Computer Science for funding this research and to LPPM University Putra Abadi Langkat and LPPM STMIK Pelita Nusantara, who support the entire research team.

6. DECLARATIONS

AUTHOR CONTIBUTION

Desi Vinsensia did the mathematical model development and literature review, Jonhariono Sihotang wrote it into draft form and improved language and writing systematics, Hengki Tamando Sihotang did mathematical modeling, developed algorithms, Siska Amari did disease initialization and provided Team with an understanding of infectious diseases. This research is a collaboration between 3 fields of science: Mathematics, Computer Science, and Health Sciences. The Institute of Computer Science funds this research.

FUNDING STATEMENT

The IOCSCIENCE Research Institute funded this research through a Basic Research Grant. Thanks to LPPM STMIK Pelita Nusantara and LPPM University Putra Abadi Langkat, who have fully supported it. Thanks also to colleagues who participated and supported us.

COMPETING INTEREST

All authors involved in completing this paper are not in a conflict of interest that results in mutual downfall. We, the authors, are very supportive of each other. Towards the journal editor, we have no interest whatsoever. We declare clean from conflicts of interest.

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