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Hybrid Multi-Objective Metaheuristic Machine Learning for Optimizing Pandemic Growth Prediction

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Abstract

Pandemic and epidemic events underscore the challenges of balancing health protection, economic resilience, and mobility sustainability. Addressing these multidimensional trade-offs requires adaptive and data-driven decision-support tools. This study proposes a hybrid framework that integrates machine learning with multi-objective optimization to support evidence-based policymaking in outbreak scenarios. Six key indicators—confirmed cases, disease-related mortality, recovery count, exchange rate, stock index, and workplace mobility—were predicted using eight regression models. Among these, the XGBoost Regressor consistently achieved the highest predictive accuracy, outperforming other approaches in capturing complex temporal and socioeconomic dynamics. To enhance interpretability, we developed SHAPPI, a novel method that combines Shapley Additive Explanations (SHAP) with Permutation Importance (PI). SHAPPI generates stable and meaningful feature rankings, with immunization coverage and transit station activity identified as the most influential factors in all domains. These importance scores were subsequently embedded into the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to construct Pareto-optimal solutions. The optimization results demonstrate transparent trade-offs among health outcomes, economic fluctuations, and mobility changes, allowing policymakers to systematically evaluate competing priorities and design balanced intervention strategies. The findings confirm that the proposed framework successfully balances predictive performance, interpretability, and optimization, while providing a practical decision-support tool for epidemic management. Its generalizable design allows adaptation to diverse geographic and epidemiological contexts. In general, this research highlights the potential of hybrid machine learning and metaheuristic approaches to improve preparedness and policymaking in future health and socioeconomic crises.

Keywords: Pandemic, Hybrid Machine Learning, Multi-Objective Optimization, Metaheuristic, SHAPPI

1. Introduction

Pandemic events have significantly disrupted global health systems, economies, and social structures [1], [2]. In various regions, even after official relaxation of community activity restrictions, fluctuating trends in confirmed cases and disease-related mortality have persisted. Historical records from major outbreaks worldwide show that millions of confirmed cases, hundreds of thousands of fatalities, and widespread vaccination campaigns can occur within relatively short timeframes. Such resurgence patterns highlight the ongoing challenges posed by emerging variants and evolving disease dynamics.

Balancing public health protection with economic resilience remains a complex undertaking. Although Non-Pharmaceutical Interventions (NPIs), such as community activity restrictions and mobility control measures, have been effective in controlling disease transmission [3], they often disrupted mobility and economic activity [4], [5], leading to job losses and social distress [6], [7] This reflects the inherent trade-offs between pandemic containment and the continuity of socioeconomic functions that policymakers must carefully navigate.

To support more balanced policies, predictive models are needed to evaluate health, economic, and mobility outcomes simultaneously [8]. Traditional epidemic models, such as SIR or SEIR, although foundational [9], lack the flexibility to account for complex interdependencies across domains [10], [11]. In contrast, machine learning and metaheuristic

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optimization techniques have shown strong capabilities in modeling nonlinear high-dimensional relationships [12], [13], enabling the optimization of competing objectives through algorithms such as GA, PSO, and SA [14], [15], [16].

However, interpretability remains a key challenge, especially in multi-objective settings within low- and middle-income countries [17], [18], [19], [20]. To bridge this gap, this study proposes a hybrid framework that integrates XGBoost, PSO, SHAP, Permutation Importance (PI), and NSGA-II to predict six key indicators and generate interpretable, policy-relevant recommendations. Although NSGA-II is widely used, its scalability poses challenges in many-objective contexts. Recent advances, such as boundary protection indicators [21], ensemble frameworks combining AdaBoost and K-means clustering [22], and dominance-controlled mechanisms [23], [24], underscore the importance of adaptive and interpretable optimization strategies for future pandemic modeling. To date, few studies have applied this hybrid approach in the Indonesian context [25]. Consequently, this research contributes to the literature by developing a comprehensive model that unifies machine learning, metaheuristics, and Explainable Artificial Intelligence (XAI) – providing a robust foundation for data-driven decision making to manage pandemic dynamics.

The main contributions of this study can be summarized as follows. We develop a comprehensive prediction framework based on the XGBoost Regressor (XGBR) that integrates multiple dimensions of pandemic impact, including public health indicators (confirmed cases, disease-related mortality, and recovery count), economic fluctuations (currency change rate and stock index movement) and mobility changes (workplace activity). To enhance predictive performance, the model employs Particle Swarm Optimization (PSO) for hyperparameter tuning, enabling robust parameter adjustment across these diverse targets. Beyond accuracy, interpretability is emphasized through the use of PI, which identifies the most influential features shaping model outcomes. To further strengthen explainability, we introduce SHAPPI, a novel hybrid method combining SHAP and PI to generate stable and interpretable feature importance scores, thus overcoming the limitations of each technique in isolation. Finally, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) is applied to extend the framework into a multiobjective optimization setting, allowing the identification of Pareto-optimal trade-offs across health, economic, and mobility objectives. Collectively, these contributions establish a hybrid, interpretable, and optimization-driven framework that provides a valuable decision support tool for policymakers to navigate the complex challenges of pandemic management.

The remainder of this paper is organized as follows: Section 2 provides a comprehensive literature review. Section 3 describes the materials and methods used in the study. Section 4 presents the experimental results, discusses the findings, and compares them with related work. Finally, Section 5 concludes the paper with key insights and outlines potential directions for future research.

2. Literature Review

2.1. Hybrid Machine Learning and Metaheuristic Approaches in Pandemic Modeling

Research on epidemic and pandemic modeling has advanced through the integration of Machine Learning (ML) and multi-objective metaheuristic algorithms. The SARS outbreak marked a pivotal milestone, as mathematical models were used to analyze transmission, forecast spread, and evaluate control strategies [26]. SARS insights informed subsequent modeling of MERS and COVID-19, demonstrating the applicability of epidemic modeling principles in different diseases. Hybrid ML–metaheuristic approaches further enhance predictive capability by capturing the complex interplay between health, mobility, and economic factors. In outbreak contexts such as MERS [27], H1N1 [28], ML models including Long-Short-Term Memory (LSTM) [29], Convolutional Neural Networks (CNN) [30], and Random Forest (RF) [31], have shown strong performance in forecasting infection trends, mortality, and spatial dynamics from temporal and spatial data.

Beyond predictive models, hybrid strategies using metaheuristics such as the non-dominated classification genetic algorithm II (NSGA-II) [32], [33], and PSO [34] have optimized multiple objectives simultaneously, including minimizing infection rates, reducing mortality, allocating limited healthcare resources, and mitigating economic disruptions. Studies such as [35], [36] emphasize the value of these frameworks to balance trade-offs under crisis conditions. Moreover, interpretability tools such as SHAP [32]. improve model transparency, while real-time data integration improves responsiveness to rapidly evolving outbreak dynamics.

2.2. Regression Modeling with Machine Learning: Development and Evaluation

Major pandemics including SARS, MERS, and H1N1 have disrupted healthcare systems, economies, and human mobility, underscoring the multidimensional nature of epidemic impacts. Economically, recessions, unemployment, and shifts in consumer behaviour were observed, with targeted recovery policies proposed by Rathnayaka et al. [37] and sustainability-oriented strategies highlighted by Piccarozzi et al. [38] From the health perspective, Clemente et al.[39] noted the exacerbation of inequalities and pressure on health infrastructure, while Jordan et al. [40] demonstrated how optimization techniques improved vaccine distribution and healthcare resource allocation. Mobility research, such as that by Zhang et al. and Mesfin et al. [41], [42], explored the effects of movement restrictions, while Biswas et al. [43] recommended adaptive, data-driven restriction policies.

Recent contributions also highlight the importance of robust and hybrid modelling frameworks. Chaerani et al. [44] discussed robust optimization in addressing uncertainty for achieving Sustainable Development Goals (SDGs) during crises, and Jamshidi et al. [45] reviewed hybrid deep learning models for pandemic forecasting. Complementary studies such as Rabaan et al. [27] on MERS-CoV dynamics, Costa et al. [28], comparing H1N1 and COVID-19, and Fajardo et al. [46] applying mathematical and ML models across outbreaks illustrate that epidemic modeling principles are transferable beyond a single disease. More recently, Zhang et al. [47] developed a universal outbreak risk prediction tool validated across multiple datasets, while Bedi et al. [48] reviewed the integration of AI with mechanistic epidemiological modeling.

Additional studies have focused on robust optimization and hybrid modelling. Chaerani et al. [44] discussed the relevance of robust optimization in addressing uncertainty in achieving SDGs during the pandemic. Jamshidi et al. [45] reviewed the application of hybrid deep learning models for forecasting pandemic trends, combining statistical rigor with AI flexibility to manage complexity and uncertainty. While significant progress has been made in applying hybrid models and incorporating real-time data, gaps remain. Many existing models focus on single-objective optimization or lack interpretability. There is a need for more comprehensive approaches that integrate explainable AI, real-time socioeconomic indicators, and multi-objective metaheuristics for more robust and actionable pandemic response strategies.

Collectively, these studies demonstrate that hybrid machine learning and metaheuristic approaches are broadly applicable to epidemic modelling, offering improvements in predictive accuracy, interpretability, and decision-making under uncertainty. This body of literature confirms that the proposed framework is validated for broader application across diverse epidemic scenarios.

3. Methodology

Figure 1 illustrates the methodological framework adapted from Pan et al. [32], consisting of five main stages: (1) data collection, (2) data pre-processing, (3) regression modeling, (4) multi-objective optimization, and (5) policy recommendation. The dependent variables comprise six key indicators, while the independent variables are classified into health, mobility, and economic factors. Pre-processing includes min-max normalization. Eight regression algorithms are applied: RFR, GBR, XGBR, SVR, DTR, ABR, KNN, and LR. Hyperparameter tuning is performed using PSO with parameters n (number of particles), d (rolling window depth), s (smoothing parameter), l (lag) and w (moving average window). The SHAPPI method, a combination of SHAP and PI, is applied to compute stable and consistent feature importance weights. These weights are integrated into the NSGA-II algorithm to generate Pareto-optimal solutions. Model performance is evaluated using RMSE, MAE, MAPE, and R-squared metrics. Each phase of the model is detailed in the following sections.

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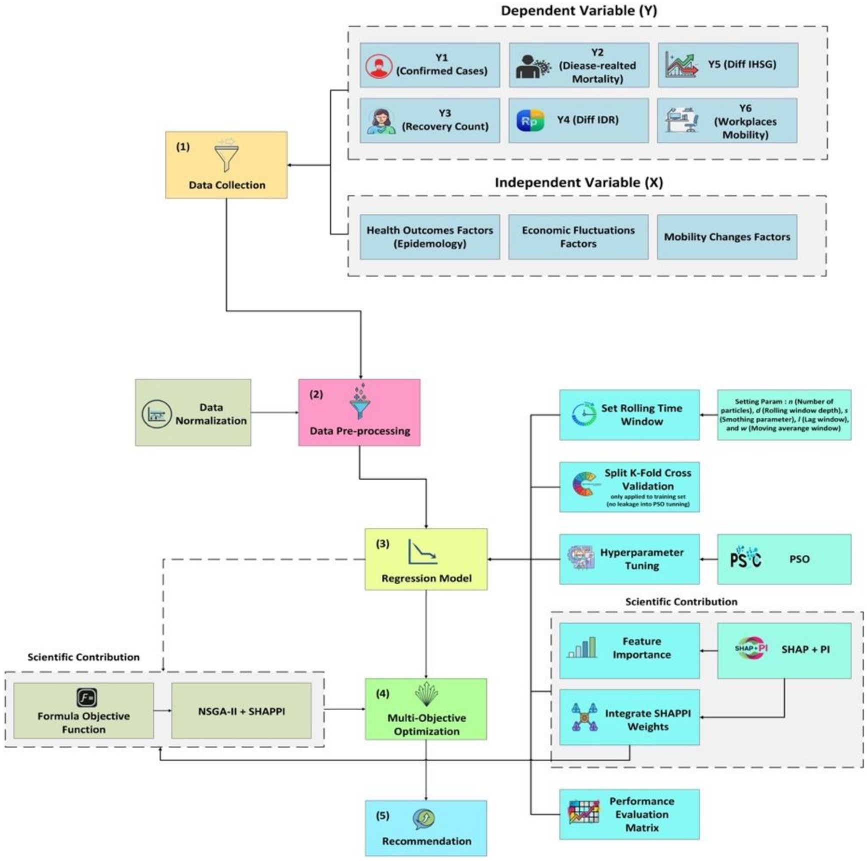

Figure 1. Methodology for implementing the recommended research.

3.1. Data Collection

This study employs the Jakarta pandemic dataset, collected during a pandemic period, which encompasses indicators related to health outcomes, economic fluctuations, and mobility changes that are pertinent to outbreak modeling. The dataset is structured to facilitate predictive modeling and multi-objective optimization, while remaining generalizable beyond a specific disease or timeframe. The independent variables (X) are organized into three categories: (1) Health outcomes, comprising vaccination coverage, healthcare workforce availability, and hospital bed occupancy, obtained from official national databases and the Central Bureau of Statistics (BPS); (2) Economic fluctuations, including the inflation rate and monetary policy rate sourced from the Central Bank and Yahoo Finance, as well as social assistance programs and minimum wage obtained from BPS; and (3) Mobility changes, derived from Google Mobility Reports, which capture variations in public activity across Jakarta. As presented in table 1, the Shapiro–Wilk test ($p < 0.001$) confirms that all variables deviate from normal distribution; consequently, the data are summarized using the median and Interquartile Range (IQR) to provide a more robust representation of central tendency and variability.

Table 1. Characteristics of features in the dataset.

Category	Feature Description	Variable	Median	IQR	[Min, Max]	P-value
Health outcomes	Hospital Bed Occupancy	X_1	23,780.00	699.00	[23,081.0, 23,780.0]	<0.001
Health outcomes	Healthcare Workforce Availability	X_2	56,853.00	17,546.00	[45,552.0, 63,098.0]	<0.001
Health outcomes	Vaccination Coverage	X_3	1,898,567.00	10,367,980.00	[0.0, 10,805,878.0]	<0.001
Mobility changes	Retail and Leisure Mobility	X_4	-24.00	20.00	[-68.0, 10.0]	<0.001

Mobility changes	Essential Services Mobility	X_5	-2.00	15.00	[-46.0, 34.0]	<0.001
Mobility changes	Visit in Parking Space	X_6	-42.00	37.00	[-96.0, 31.0]	<0.001
Mobility changes	Public Transport Mobility	X_7	-36.00	18.00	[-79.0, 6.0]	<0.001
Mobility changes	Residential Mobility	X_8	10.00	6.00	[-1.0, 34.0]	<0.001
Economic fluctuations	Inflation Rate	X_9	1.66	1.27	[0.91, 4.61]	<0.001
Economic fluctuations	Monetary Policy Rate	X_{10}	3.50	0.50	[3.5, 4.75]	<0.001
Economic fluctuations	Social Assistance Programs	X_{11}	5.29e+11	4.92e+11	[3.97e+10, 5.31e+11]	<0.001
Economic fluctuations	Minimum Wage	X_{12}	4,416,186.00	374,505.00	[4,267,349.0, 4,641,854.0]	<0.001

To ensure data quality and representativeness, the selected variables reflect empirically grounded indicators that are widely used by national agencies. Health-related data provide information on pandemic response capacity, while economic and mobility indicators offer consistent metrics to assess broader societal impact. DKI Jakarta, as Indonesia's capital and early epicenter of the pandemic, maintains the most comprehensive and timely data infrastructure. Its data sets are routinely used by ministries for the formulation of national-level policies. Therefore, while the study focuses on Jakarta, its data serve as a valid national reference to model the response to the pandemic and inform socioeconomic recovery strategies.

3.2. Data Pre-processing

The variables X are Min Max scaled in the pre-processing phase. The scaler is a method used to adjust the scale of a dataset [49]. Scalers are helpful when you have data on different scales and want to customize it to make it easier to analyze. This method adjusts the data scale by changing the data values to values between 0 and 1 [50]. Then, Scaler compares the data more efficiently and avoids bias due to different scales [51]. The data will then be split using the K-fold cross-validation process. Cross-validation of K-Folds is a data validation technique used to evaluate the performance of machine learning models [52]. Cross-validation of K times was used to assess the consistency of the model [53]. This method divides the training data into k parts or k times and uses k=3 characteristics to train the model and a factor to test the model. This procedure is performed k times, and each segment is used as test data once. The outcome is the average precision of the k tests [52].

3.3. Regression Modeling with Machine Learning: Development and Evaluation

This study applies eight regression-based machine learning models RFR, GBR, XGBR, SVR, DTR, ABR, KNR, and LR to predict six key pandemic indicators: confirmed cases (Y1), disease-related mortality (Y2), recovery count (Y3), diff-idr (Y4), diff-ihsg (Y5), and workplace mobility (Y6). Each target is treated independently to allow tailored hyperparameter tuning across health, economic, and mobility dimensions. Avoid combining SI and CGS units, such as current in amperes and magnetic field in oersted's. This often leads to confusion because equations do not balance dimensionally. If you must use mixed units, clearly state the units for each quantity that you use in an equation.

Each model has specific strengths: ensemble methods like RFR, GBR, and XGBR capture complex patterns and offer high accuracy [54], [55]; SVR handles high-dimensional data well [56]; DTR provides interpretability [57]; ABR focuses on hard-to-predict samples [58]; KNR captures local patterns [59]; and LR offers a simple baseline [3],

To improve the performance and generalizability of the model, hyperparameter tuning was performed using the PSO algorithm [32]. PSO is recognized for its efficiency in exploring large solution spaces with relatively low computational complexity [60]. The tuning process begins by initializing a population of particles, where each particle represents a candidate solution, a specific combination of hyperparameters. Each particle evaluates its position based on an objective function, typically the prediction error, assessed using metrics such as R-squared (R2), RMSE, MAE and MAPE.

The model in this study was validated using consistent three-fold cross-validation throughout both the modeling and optimization phases to mitigate overfitting and enhance generalizability. Although an independent out-of-sample test set was not available, such cross-validation-based evaluation is a well-established practice in predictive modeling using historical data [61], [62]. K-fold cross-validation has been shown to yield favorable results even in time series settings when adapted appropriately [63]. Furthermore, consistent cross-validation remains a reliable alternative when blocked or time-sensitive strategies are infeasible due to data limitations [64]. Although cross-validation may not capture all forms of overfitting - especially in highly complex models - its integration with hyperparameter tuning, such as the PSO optimization used in this study, represents a multifaceted approach recommended for robust model evaluation [32].

The final evaluation metrics, including MAE, RMSE, MAPE and R2, were calculated in the holdout test set to assess the model performance. To ensure robustness and avoid overfitting, three-fold cross-validation is used [32], in which each configuration is evaluated on three different data subsets and the results are averaged. During the iterative process, PSO updates the velocity and position of each particle by learning from the best-performing individuals and the best global solution in the population. This enables the swarm to gradually converge toward optimal hyperparameter configurations for each model. The final regression models obtained through PSO tuning are then thoroughly evaluated to ensure stable, accurate, and reliable prediction performance across various pandemic-related outcomes.

3.3.1. The Proposed SHAPPI: A Hybrid Feature Importance Method Combining SHAP and PI

This study introduces SHAP–Permutation Importance (SHAPPI) a hybrid explainability method that integrates the local interpretability of SHAP values with the global robustness of PI. While SHAP quantifies the marginal contribution and polarity of each feature based on Shapley values from cooperative game theory [65], [66], PI evaluates the sensitivity of model performance to feature perturbations through random permutation [67]. Each method has its strengths: SHAP offers detailed information on individual predictions, while PI reflects the impact of global features. However, each also has limitations when used independently.

SHAPPI addresses these limitations by combining both approaches into a unified scoring mechanism. It produces three outputs per feature: (1) the polarity score n, which shows whether the impact of a feature is positive or negative; (2) the error score e, derived from permutation-based performance degradation; and (3) the aggregate score a, calculated by normalizing and integrating the SHAP and PI scores [68]. The result is a balanced, interpretable, and robust importance score.

The SHAPPI procedure. Given a set of characteristics x, a target y, and a model m, the algorithm calculates the SHAP value sf and the PI score pf for each characteristic f. These are normalized and combined to produce the final importance score a_f A normalization step ensures comparability across features, with final weights rescaled to sum to one. These weights are stored in a dictionary for use in model interpretation or optimization. The complete pseudocode and implementation are detailed in the availability section.

3.3.2. Mathematical Formulation of SHAPPI Values

SHAPPI combines the local interpretability of SHAP values and the global robustness of PI into a unified feature importance score. SHAP assigns a contribution score to each feature by averaging its marginal effect across all possible subsets of features. Let N be the set of all features, and f(x) the prediction of the model. The SHAP value for feature f, denoted sf, is calculated using Formula (1):

$$s_f = \sum_{S \subseteq N \setminus \{f\}} \frac{|S|!\,(|N| - |S| - 1)!}{|N|!} [f(S \cup \{f\}) - f(S)] \tag{1}$$

SHAP values satisfy key properties of cooperative game theory, including efficiency, symmetry, and additivity [65], [69]. PI quantifies the sensitivity of a model to a feature by measuring performance degradation after random permutation. Given the original model performance r and the performance after the permutation feature f, denoted rf, the PI is calculated using formula (2):

$$p_f = 1 - \frac{r_f}{r} \tag{2}$$

In Formula (2), this score can be normalized using the Min-Max scaling to align with the SHAP scores. The SHAPPI score for a feature f, denoted a_f, integrates both SHAP and PI scores to produce a balanced importance estimate. This hybrid score is defined in formula (3):

$$a_f = \frac{\widehat{s_f} + \widehat{p_f}}{2} \tag{3}$$

In Formula (3) represents $\widehat{s_f}$ and $\widehat{p_f}$ are the normalized SHAP and PI scores, respectively.

Theorem 1 (Properties of SHAPPI). SHAPPI combines the strengths of SHAP and PI by inheriting the interpretability of the former and the empirical robustness of the latter. Through this integration, SHAPPI enhances the stability in feature attribution by uniting two complementary methods that address different aspects of explainability. It mitigates bias by reducing the susceptibility of PI to categorical dominance while simultaneously overcoming the model-agnostic limitations often associated with SHAP. As a result, SHAPPI offers more comprehensive insights into the relevance of features by capturing both local and global perspectives, thereby providing stakeholders with a balanced and reliable interpretability framework.

3.4. Multi-Objective Optimization Using NSGA-II with SHAPPI

This section presents a multi-objective optimization framework using NSGA-II to model trade-offs among six pandemic-related outcomes, guided by SHAPPI-derived feature weights. The optimization seeks to minimize adverse outcomes (e.g., confirmed and mortality cases) and maximize favourable indicators (e.g., recovery and workplace mobility).

3.4.1. Objective Definition

Each objective function Fj is formulated as a weighted sum of input features xi using SHAPPI importance scores $w_{i,j}$

$$F_j = \sum_{i=1}^{n} w_{i,j} \cdot x_i, \quad j = 1, \dots, 6 \tag{4}$$

Formula (4) represents each individual objective function F_j, where the summation captures the contribution of each feature x_i, weighted by its corresponding SHAPPI importance $w_{i,j}$ for the j-th objective (e.g., positivity rate, mortality, economic indicators, etc.). The vector of objectives is:

$$\mathrm{F(x)} = [\mathrm{F_1(x), F_2(x), \dots, F_6(x)}] \tag{5}$$

Formula (5) defines the multi-objective function vector, with each component representing a distinct target metric to be minimized simultaneously within the optimization process.

3.4.2. Optimization Formulation

The goal is to minimize the six objectives subject to bounds $x_i \in [x_l, x_u]$, where $(x_l = 0)$ and x_u is the maximum observed value for each feature. The formulation (6) is:

$$\begin{gathered} Minimize: \boldsymbol{F}(\boldsymbol{x}) \\ Subjectto: x_i \in [x_l, x_u], \quad \forall i = 1, \dots, n \end{gathered} \tag{6}$$

3.4.3. NSGA-II Implementation

The NSGA-II is applied with the following configuration: population size = 500, crossover probability = 0.5, mutation probability = 0.2, and 100 generations. Simulated Binary Crossover (SBX) and Polynomial Mutation (PM) are used for genetic operations. Tournament selection guides evolutionary progression [32].

3.4.4. Model Components.

The formulation of the model is structured around three main components: objective functions, decision variables, and model parameters with their corresponding constraints. These components work together to capture the complexity of pandemic dynamics across health, economic, and mobility dimensions. The objective functions (table 2) cover health

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indicators such as confirmed cases, disease-related, and recovery count, along with economic indicators including exchange rate fluctuations and stock index movements, and workplace mobility.

Table 2. Objective Functions

Feature	Name Feature
Y_1	Confirmed Cases
Y_2	Disease-related mortality
Y_3	Recovery Count
Y_4	Difference in IDR Exchange Rate (diff-idr)
Y_5	Difference in IHSG Index (diff-ihsg)
Y_6	Workplace Mobility

The decision variables (table 3) represent controllable factors such as healthcare capacity, vaccination coverage, different types of mobility, and socio-economic indicators like inflation, monetary policy, social assistance, and minimum wage.

Table 3. Decision Variables

Feature	Name Feature
X_1	Hospital Bed Occupancy
X_2	Healthcare Workforce Availability
X_3	Vaccination Coverage
X_4	Retail and Leisure Mobility
X_5	Essential Services Mobility
X_6	Visit in Parking Space
X_7	Public Transport Mobility
X_8	Residential Mobility
X_9	Inflation Rate
X_{10}	Monetary Policy Rate
X_{11}	Social Assistance Programs
X_{12}	Minimum Wage

Parameters and constraints (table 4) ensure that the input values remain within realistic limits, define the weighting of each objective, and provide an evaluation function to assess Pareto-optimal solutions using NSGA-II. This formulation enables the model to capture the complexity of pandemic dynamics while producing balanced trade-offs between health, economic, and mobility objectives.

Table 4. Model Parameters and Constraints

Parameter and Constraints	Description
$\mathbf{x_l}$	Lower bounds for input variables, set to zero in this study
$\mathbf{x_u}$	Upper bounds for input variables, defined as the maximum values in dataset X
$\mathbf{Y}_{weights}$	Weight dictionary for each target variable (Y_1 to Y_6) used in weighted fitness computation.
F_{Y_f}	Weighted fitness function for each objective function F_{Y_f}, computed as the sum of feature
F	Matrix containing all objective functions to be optimized using NSGA-II.

F_eval	Evaluation metric for analyzing Pareto-optimal solutions, computed as the product of selected objective function pairs.

3.4.5. Pareto Analysis

NSGA-II yields a Pareto front of trade-off solutions X* and their corresponding objective values F*. Trade-offs are evaluated using a composite measure:

$$F_{\text{eval}} = F_x \cdot F_y \quad (7)$$

In Formula (7) represents F_x and Fy are selected pairs of objectives. Lower values of F_{eval} suggest better compromises, supporting multi-criteria decision-making.

3.4.6. Model Parameters and Constraints

All parameters and variable definitions are detailed in table 4. The model uses SHAPPI scores to ensure optimization is interpretable and data-driven.4. Results and Discussion

4. Results and Discussion

4.1. Result

4.1.1. Regression Model Performance and PSO-Based Optimization for Pandemic Prediction

The proposed model demonstrated strong predictive performance across multiple key indicators spanning public health, economic stability, and population mobility. For health-related metrics, it accurately predicted positivity rates, disease-related mortality, and recovery counts, enabling timely and informed outbreak management. Economic indicators, including currency exchange rate fluctuations and stock market index changes, were also forecasted with high accuracy, providing valuable insights for balancing economic resilience with public health interventions.

Additionally, the model effectively captured mobility trends during outbreak periods, such as changes in workplace mobility and transportation activity, which are critical for assessing the effectiveness of intervention measures. To achieve these results, eight regression models RFR, GBR, XGBR, DTR, SVR, KNN, ABR, and LR were implemented to predict six key indicators: confirmed cases (Y1), disease-related mortality (Y2), recovery count (Y3), diff-idr (Y4), diff-ihsg (Y5), and workplace mobility (Y6). Following the configuration by Pan et al. [32], the hyperparameter search space includes: number of estimators (n) within [5, 50], tree depth (d) within [5, 50], minimum data for split (s) in [2, 50], leaf size (l) in [1, 20], and rolling time window size (w) in $\{3, 5, 7\}$. The rolling time window technique enables dynamic modelling of temporal dependencies by capturing short-term trends and maintaining the sequential integrity of the data [70], [71]. This method ensures that predictions are consistently based on the most recent information, allowing the model to respond effectively to sudden changes and evolving patterns [72].

To further enhance predictive accuracy, the window size is treated as a tuneable hyperparameter. Optimization is performed using PSO, a metaheuristic algorithm recognized for its capability in efficiently navigating complex search spaces and achieving rapid convergence [32]. The comparative results presented in figure 2 demonstrate the superiority of PSO over other tuning methods such as Genetic Algorithm, Grid Search, and Random Search highlighting its robustness across various prediction targets.

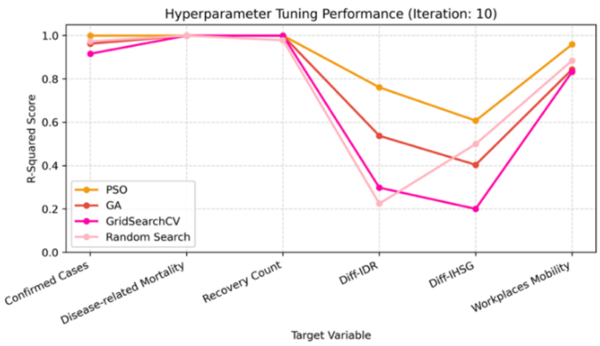

Figure 2. Hyperparameter Tuning Performance

Model performance is evaluated using five metrics: R^2, RMSE, MAE, MAPE, and MSE, with a 3-fold cross-validation approach. As shown in figure 3, XGBR consistently achieved the lowest RMSE rank across all prediction targets. Statistical validation using the Friedman test yielded a p-value of 0.00011, indicating significant differences among models, with XGBR outperforming others in nearly all prediction tasks.

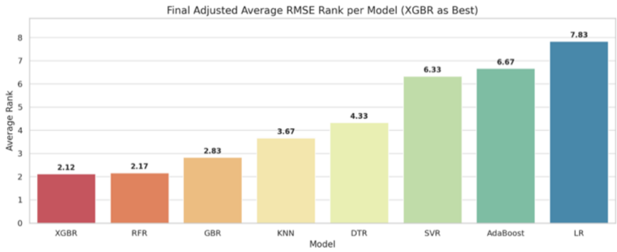

Figure 3. Visualization of the Friedman test results comparing average RMSE ranks across all models for eight target variables.

The test reveals statistically significant differences in model performance ($p < 0.05$), confirming that XGBR consistently achieves superior rankings compared to baseline regressors. While other ensemble methods such as GBR and RFR also exhibit strong predictive capabilities, XGBR emerges as the most reliable model, with superior performance across health, economic, and mobility domains. Table 5 confirms that XGBR achieved the lowest error values such as an RMSE of 0.0126 and a MAPE of 0.0290 for mortality prediction demonstrating its reliability and generalization capability. Conversely, linear models like LR and weak ensemble methods like AdaBoost exhibit lower performance, especially for complex targets such as exchange rate and stock index variation. Overall, the PSO-optimized XGBR model stands out as a strong candidate for supporting pandemic management through accurate and stable predictions.

Table 5. Overall predictive performance of regression models across six target variables.

No	Model	Target	R-square	RMSE	MSE	MAE	MAPE
1	GBR	Disease-related Mortality	0.9999	0.0104	0.0001	0.0086	0.0362
2	XGBR	Disease-related Mortality	0.9999	0.0126	0.0001	0.0039	0.0290
3	RFR	Disease-related Mortality	0.9999	0.0088	0.0001	0.0042	0.0304
4	DTR	Disease-related Mortality	0.9999	0.0108	0.0001	0.0049	0.0330
5	SVR	Disease-related Mortality	0.9955	0.0678	0.0046	0.0559	0.3789
6	KNN	Disease-related Mortality	0.9999	0.0120	0.0001	0.0054	0.0292
7	AdaBoost	Disease-related Mortality	0.9977	0.0478	0.0023	0.0360	0.0655
8	LR	Disease-related Mortality	0.9819	0.1355	0.0183	0.1027	0.2696
9	GBR	Confirmed Cases	0.9904	0.1054	0.0112	0.0495	0.2140
10	XGBR	Confirmed Cases	0.9932	0.0889	0.0079	0.0434	0.2302
11	RFR	Confirmed Cases	0.9906	0.1045	0.0109	0.0515	0.2464
12	DTR	Confirmed Cases	0.9928	0.0912	0.0083	0.0443	0.2149
13	SVR	Confirmed Cases	0.7252	0.5646	0.3188	0.2504	0.6194
14	KNN	Confirmed Cases	0.9860	0.1273	0.0162	0.0558	0.4823
15	AdaBoost	Confirmed Cases	0.8838	0.3670	0.1347	0.2993	2.6489
16	LR	Confirmed Cases	0.4668	0.7856	0.6185	0.5605	2.5717
17	GBR	Recovery Count	0.9989	0.0128	0.0002	0.0097	0.0217
18	XGBR	Recovery Count	0.9999	0.0079	0.0001	0.0041	0.0161

19	RFR	Recovery Count	0.9999	0.0130	0.0001	0.0070	0.0127
20	DTR	Recovery Count	0.9998	0.0142	0.0002	0.0066	0.0268
21	SVR	Recovery Count	0.9944	0.0752	0.0057	0.0610	0.0949
22	KNN	Recovery Count	0.9999	0.0114	0.0001	0.0059	0.0244
23	AdaBoost	Recovery Count	0.9973	0.0521	0.0027	0.0436	0.1060
24	LR	Recovery Count	0.9731	0.1655	0.0274	0.1269	0.2744
25	GBR	Diff_idr	0.7152	0.5190	0.2694	0.2621	0.4706
26	XGBR	Diff_idr	0.7612	0.4753	0.2259	0.2329	0.5510
27	RFR	Diff_idr	0.7122	0.5218	0.2723	0.2690	0.5152
28	DTR	Diff_idr	0.5899	0.6228	0.3879	0.2917	0.7252
29	SVR	Diff_idr	0.3716	0.7710	0.5944	0.4328	0.8684
30	KNN	Diff_idr	0.7136	0.5205	0.2709	0.2547	0.5077
31	AdaBoost	Diff_idr	0.2648	0.8509	0.7240	0.4716	0.1649
32	LR	Diff_idr	0.2608	0.8362	0.6992	0.5350	1.2516
33	GBR	Diff_ihsg	0.6962	0.5431	0.2950	0.3672	1.5172
34	XGBR	Diff_ihsg	0.6076	0.6173	0.3811	0.3774	1.7117
35	RFR	Diff_ihsg	0.7071	0.5388	0.2903	0.3577	1.3403
36	DTR	Diff_ihsg	0.3279	0.8078	0.6526	0.4816	2.0138
37	SVR	Diff_ihsg	0.3263	0.8088	0.6541	0.5834	1.7768
38	KNN	Diff_ihsg	0.6693	0.5666	0.3211	0.3658	1.3854
39	AdaBoost	Diff_ihsg	0.2662	0.8628	0.7444	0.6363	2.4853
40	LR	Diff_ihsg	0.1075	0.9309	0.8666	0.6969	2.4692
41	GBR	Workplaces Mobility	0.9513	0.2319	0.0538	0.1095	0.5384
42	XGBR	Workplaces Mobility	0.9593	0.2121	0.0450	0.1033	0.5302
43	RFR	Workplaces Mobility	0.9525	0.2224	0.0494	0.1036	0.6280
44	DTR	Workplaces Mobility	0.9316	0.2749	0.0756	0.1448	0.6235
45	SVR	Workplaces Mobility	0.8607	0.3900	0.1521	0.2180	4.1055
46	KNN	Workplaces Mobility	0.9474	0.2411	0.0581	0.1099	0.6103
47	AdaBoost	Workplaces Mobility	0.8356	0.4247	0.1803	0.3154	2.5492
48	LR	Workplaces Mobility	0.8360	0.4256	0.1812	0.2674	1.2064

4.1.2. Feature Importance Analysis with SHAPPI

To enhance model interpretability, we assess the importance of independent variables using XGBR in combination with SHAP, PI, and the proposed SHAPPI method. SHAP captures the polarity and marginal contribution of each feature, while PI measures the sensitivity of model predictions to feature permutation. SHAPPI integrates both perspectives to provide a more balanced attribution. Figure 4(a) to figure 4(h) present comparative feature importance visualizations across four target variable scenarios. Each scenario includes a polarity line plot and a stability bean plot.

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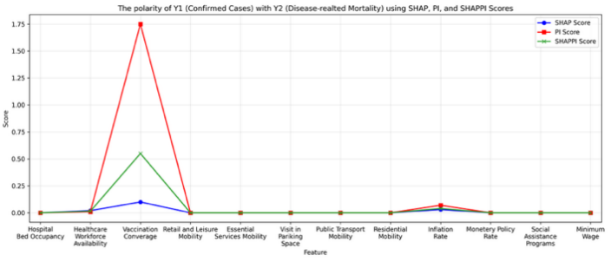
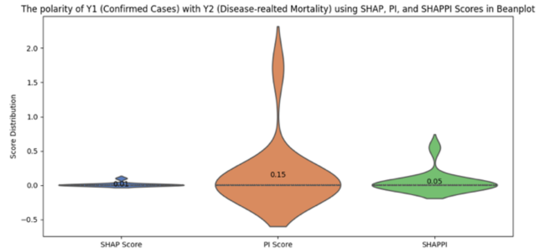
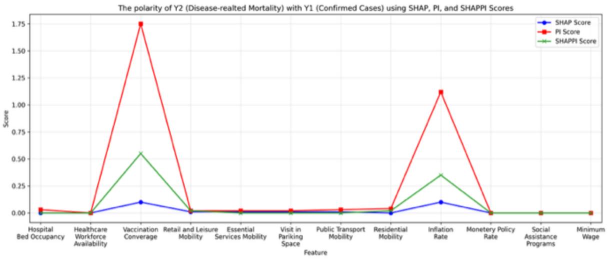


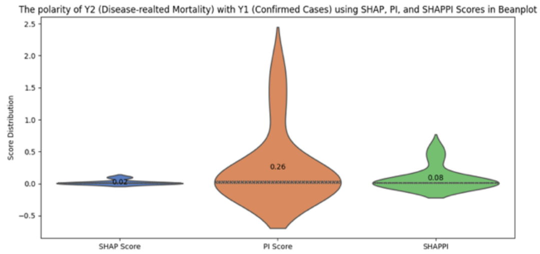
(a) Scenario 1a: Target Variables Y1 with Y3



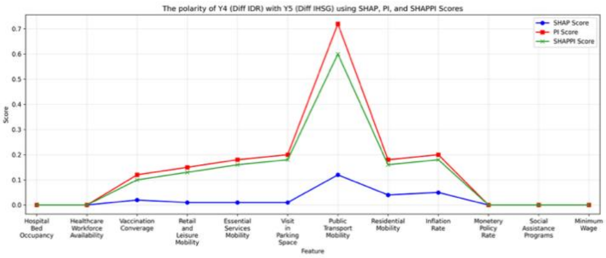
(b) Scenario 1b: Beanplot for Y1 with Y3



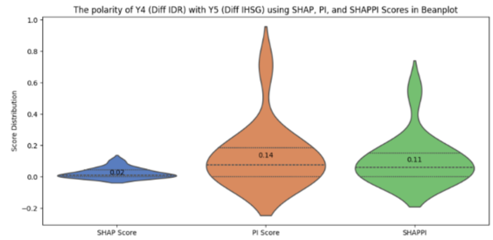
(c) Scenario 2a: Target Variables Y2 with Y1



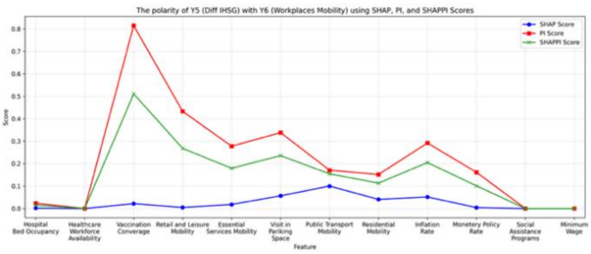
(d) Scenario 2b: Beanplot for Y2 with Y1



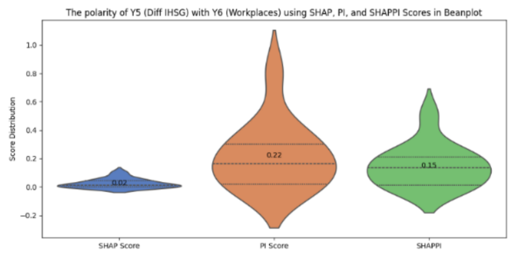
(e) Scenario 3a: Target Variables Y4 with *Y5*



(f) Scenario 3b: Beanplot for Y4 vs Y5



(g) Scenario 4a: Target Variables Y5 with Y6



(h) Scenario 4b: Beanplot for Y5 vs Y6

Figure 4. Comparative visualization of feature importance using SHAP, PI, and SHAPPI across four scenarios. Each row illustrates one scenario with its corresponding lineplot (left) and beanplot (right)

Results indicate that SHAP tends to produce conservative scores cantered near zero, underestimating feature impact. In contrast, PI highlights dominant features but suffers from high variance, particularly for variables like vaccination converge and inflation rate. SHAPPI consistently demonstrates moderate and stable importance values (range: 0.05–0.26), mitigating the extremes of SHAP and PI. In Scenario (1b) and (2b), SHAPPI moderates the inflated effect of vaccination converge and public transport mobility features observed in PI. In Scenario (3) and (4), SHAPPI effectively highlights the contribution of economic and mobility-related variables, offering improved interpretability over SHAP's underestimation and PI's volatility.

Figure 5 extends the comparative evaluation of PI, SHAP, and SHAPPI by presenting feature importance rankings for each target variable Y1 to Y6 in a unified bar plot visualization. This figure provides a clearer understanding of how individual features contribute to model predictions across various interpretability methods.

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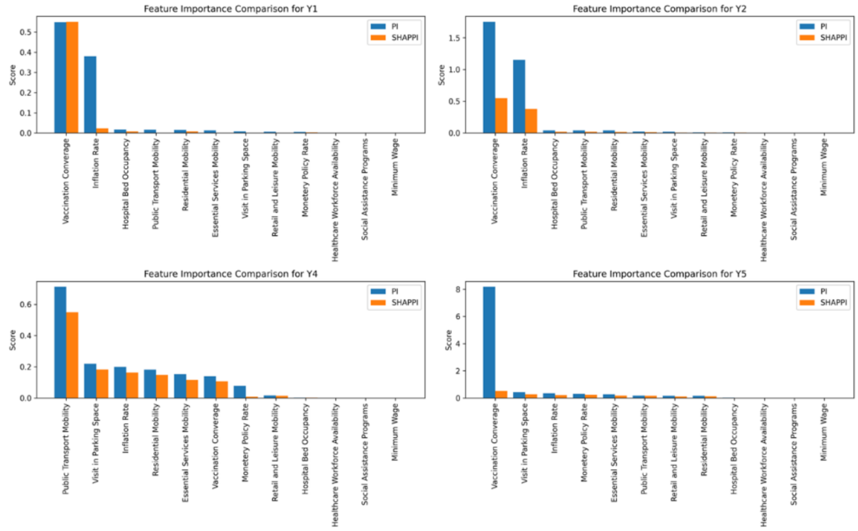


Figure 5. Comparison of Feature Importance Rankings using PI, SHAP, and SHAPPI Methods across Four Pandemic Prediction Targets.

The results indicate that the vaccination coverage is the most influential factor, consistently ranking highest in multiple targets, particularly Y1, Y2, and Y5. This highlights the critical role of vaccination coverage in shaping public health outcomes, as well as socioeconomic behaviors that may be affected during various crisis situations. The inflation rate follows closely, exerting a significant impact on nearly all targets (Y1, Y2, Y4 and Y5), suggesting that economic conditions, such as growth slowdowns, unemployment, and exchange rate volatility, affect not only financial indicators, but also health outcomes and population mobility patterns.

In addition, mobility-related variables such as public transport mobility, outdoor space visits, and retail and leisure mobility emerge as important indicators, especially for Y4 and Y5, underscoring the role of population movement in explaining economic changes and behavioral responses during public health crises or other large-scale disruptions. Meanwhile, variables such as hospital bed occupancy and residential mobility demonstrate a moderate level of importance, reflecting that healthcare capacity and living environments remain relevant, although not always dominant, in different crisis scenarios.

4.1.3. Optimal Control Strategy Determination through XGBR–NSGA-II and SHAPPI Integration

Finally, to determine optimal control strategies in pandemic modelling, this study proposes an innovative integration of the SHAPPI method into the XGBR–NSGA-II framework. The process begins with training an optimized XGBR model, in which hyperparameter tuning is performed using PSO to enhance predictive performance on six key pandemic-related targets.

The key innovation lies in the role of SHAPPI a hybrid explainability method that combines SHAP and PI which serves as an interpretability layer between the predictive model and the optimization process. As illustrated in Algorithm 1, SHAPPI is used to calculate the feature-weighted contributions for each objective function. These weights are aggregated into directed fitness functions per target, which are then combined into a multi-objective function and optimized using the NSGA-II.

Subsequently, the optimized XGBR model is integrated into the NSGA-II framework to generate Pareto-optimal solutions that balance trade-offs among the dimensions of health outcomes or epidemiology (Y1–Y3), economic fluctuations (Y4–Y5), and mobility changes (Y6) collectively representing the policy trilemma in crisis situations. As shown in figure 6, the Pareto front presents a set of non-dominated solutions that reflect optimal compromises, enabling the formulation of adaptive policies such as determining the timing of mobility restrictions while maintaining public health and economic resilience.

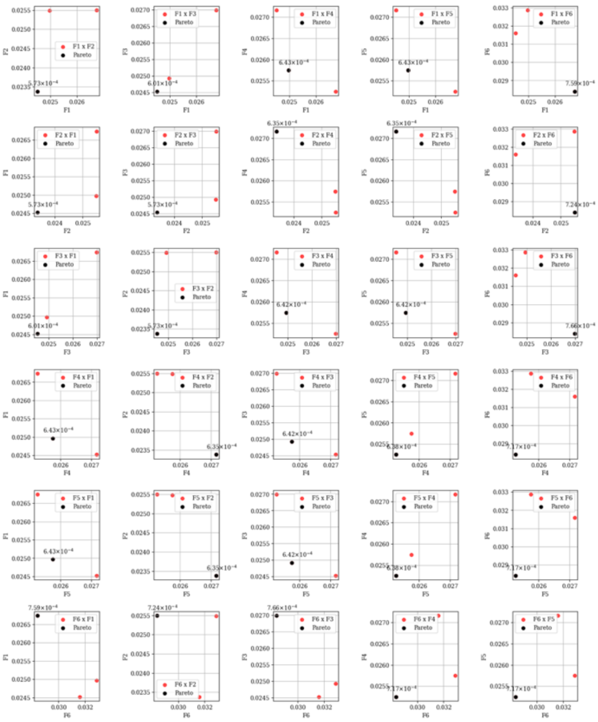


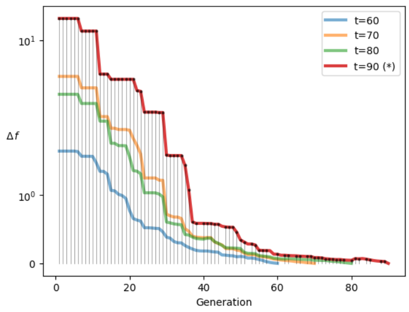
Figure 4. XGBR: The Pareto Front results from the NSGA-II Algorithm's multi-objective optimization issue for reducing health outcomes, economic fluctuations, and mobility changes.

The optimal decision variable values derived from the XGBR–NSGA-II model are presented in table 6. The most influential factors are Minimum Wage (X12, 1.290) and Social Assistance Programs (X11, 0.656), both of which play a critical role in strengthening economic resilience during crises. Moderate contributions are observed for the Monetary Policy Rate (X10), Public Transport Mobility (X7), Residential Mobility (X8), and Inflation Rate (X9). In contrast, health-related characteristics such as the Immunization Rate (X3) and the availability of the healthcare workforce (X2) exert minimal influence, while the Visit in Parking Space (X6) emerge as the least significant variable.

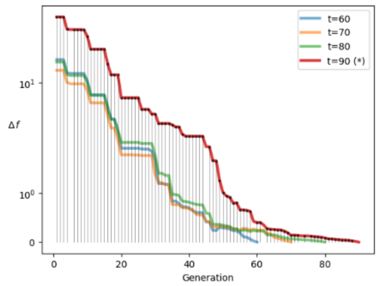
Table 6. XGBR: Setting Decision Variables Values to Provide the Most Optimum Solution.

Feature	Name Feature	Value
X_{12}	Minimum Wage	1.290482
X_{11}	Social Assistance Programs	0.655766
X_{10}	Monetary Policy Rate	0.144302
X_7	Public Transport Mobility	0.103463
X_8	Residential Mobility	0.097496
X_9	Inflation Rate	0.086446
X_4	Retail and Leisure Mobility	0.031760
X_5	Essential Services Mobility	0.027200
X_1	Hospital Bed Occupancy	0.018008
X_3	Vaccination Converage	0.012424
X_2	Healthcare Workforce Availability	0.011807
X_6	Visit in Parking Space	0.001350

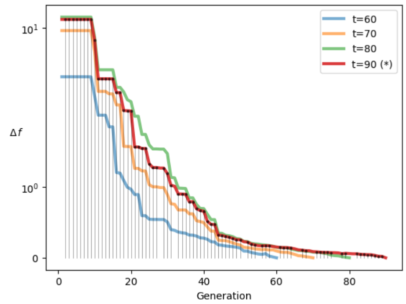
The convergence behaviour of the optimization process is evaluated and visualized in figure 7. Comparisons between SHAPPI, SHAP, and PI (figure 7(a) – figure 7(c)) show that SHAPPI achieves the fastest and most stable convergence, reducing Δf from 10^1 to near-zero within 50 generations, with the shortest computation time of 10.50 second. SHAP converges more slowly with oscillations, while PI shows the slowest and most unstable convergence behaviour.



(a) Convergence of NSGA-II with SHAPPI



(b) Convergence of NSGA-II with SHAP



(c) Convergence of NSGA-II with PI

Figure 5. Comparison of NSGA-II convergence using SHAPPI, SHAP, and PI.

4.2. Discussion

This study offers two main innovations compared to previous optimization approaches in a body of research that employed NSGA-II, SPEA-II, or MOGWO [73], [74], [75], [76]. First, we propose SHAPPI, a hybrid explainability method that integrates SHAP and PI to address the limitations of each technique and generate more stable and interpretable feature importance rankings. Second, SHAPPI is directly embedded into the multi-objective optimization process using NSGA-II, enabling the development of adaptive and data-driven policy recommendations.

The findings indicate that crises extend beyond public health concerns to generate substantial shocks to economic and mobility indicators. Feature importance analysis reveals that economic volatility—particularly in exchange rates and financial markets—is strongly influenced by changes in public and workplace mobility patterns, as well as policy interventions. For example, mobility restrictions have been shown to intensify pressures on monetary stability, while shifts in workplace productivity trigger rapid responses in capital markets. Importantly, these dynamics should not be interpreted as specific to a single crisis; instead, they reflect broader systemic patterns observable during pandemics, natural disasters, and sociopolitical instabilities. Consequently, the results underscore the inherent vulnerability of socio-economic systems to sudden disruptions and highlight the necessity of developing resilience-oriented strategies to mitigate the multidimensional impacts of future crises.

SHAPPI is validated through both theoretical formulation and empirical evaluation. As described in the mathematical theorem, this method combines the local interpretability of SHAP with the global robustness of PI into a unified scoring scheme. From an empirical perspective, SHAP has previously been proven effective in improving model transparency and operational insights when applied to real-world datasets capturing health, economic, and mobility disruptions induced by large-scale crises, including pandemics, epidemics, and other public health emergencies [77]. The comparative experiments that we conducted, as presented in the corresponding figures, confirm that SHAPPI produces more stable and balanced scores of importance of characteristics compared to SHAP or PI individually.

Furthermore, the sensitivity of SHAP to variation in iterations in complex models has been a recognized concern in the literature, reinforcing the need for robustness testing and consistent interpretations, as noted by [77]. By integrating

SHAPPI into the NSGA-II optimization framework, our approach not only improves interpretability in trade-off solutions but also accelerates and stabilizes the convergence process. This contribution aligns with comparative explainability studies that highlight differences in interpretability and visualization results, helping practitioners select the most appropriate tool for their application context. The general framing of our approach ensures its applicability in analyzing health, economic, and mobility impacts from diverse crisis scenarios, rather than being confined to a single disease context [78].

4.2.1. Generalizability and Policy Relevance

The proposed framework, although tested using Indonesian data sets, is adaptable to international application by substituting localized indicators such as exchange rates, mobility trends, or health metrics. Incorporating diverse pandemic modeling approaches allows generalization between geographies. This structure allows scenario-based simulations and aligns with locally available data formats, supporting applicability for urban health governance across regions.

4.2.2. Limitations

This study assumes static time series windows and does not consider real-time data drift. In addition, the SHAPPI method used in this research is currently limited to structured tabular data and has not yet been fully optimized for dynamic time series analysis. This study focuses on a regression-based prediction approach, rather than classification or forecasting, aiming to estimate continuous values of the observed indicators. Another limitation is that the model was trained and tested exclusively on data from the Jakarta region. Therefore, future studies are encouraged to conduct external validation using data from other regions in Indonesia to evaluate the model's generalizability.

5. Conclusion

This study presents a hybrid framework that combines XGBoost Regression (XGBR) with NSGA-II for multi-objective pandemic modeling, enhanced by the SHAPPI interpretability method. By integrating SHAP and Permutation Importance, SHAPPI provides stable and interpretable feature attributions to support data-driven decision-making in outbreak scenarios. The results reveal that fiscal and socioeconomic variables—such as minimum wage, social assistance, and interest rates—have a stronger influence on policy trade-offs during health crises than healthcare capacity alone. Features such as immunization coverage, population mobility, and inflation consistently rank highest, underscoring the importance of integrative policies that extend beyond health infrastructure. In summary, economic support and mobility regulation appear to be more impactful than solely expanding health services. The proposed framework effectively balances predictive performance, interpretability, and multi-objective optimization. Although the model was demonstrated using data from a specific region, it can be adapted for broader applications in diverse geographic and epidemiological contexts by adjusting local variables. Furthermore, embedding SHAPPI into the optimization loop improves transparency and trust, making the framework suitable for real-time, explainable, and adaptive policymaking in both health and economic crisis management.

5.1. Future Research Directions

Future enhancements include incorporating streaming data and adaptive learning for dynamic modeling. Interpretability can be advanced through reinforcement learning–driven explanations or real-time SHAPPI scoring. Comparative evaluations with MOEA/D or SPEA2 are necessary for robustness assessment. To further demonstrate the adaptability of the framework in various types of crises, future work should explicitly validate the model using data sets from multiple outbreak scenarios, such as SARS, MERS or H1N1, as well as simulated epidemic and other large-scale crisis scenarios. This approach will help assess the performance of the model in various epidemiological and socioeconomic conditions, ensuring its applicability beyond a single disease context.

The framework may also be extended to other forms of crises, such as natural disasters or socioeconomic shocks, by adjusting input variables to reflect the nature of the disruption. External validations in diverse regions and evaluation under data drift remain essential to improve model generalizability and reduce overfitting. By maintaining a general crisis-oriented design, the methodology can serve as a decision support tool for policymakers to manage health, economic, and mobility challenges in a wide range of future emergencies.

6. Declarations

6.1. Author Contributions

Conceptualization: T., Y., S.; Methodology: S.; Software: T.; Validation: T., S., and Y.; Formal Analysis: T., S., and Y.; Investigation: T.; Resources: S.; Data Curation: S.; Writing Original Draft Preparation: T., S., and Y.; Writing Review and Editing: S., T., and Y.; Visualization: T. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The dataset used in this study is not publicly available due to ethical restrictions. However, data supporting the findings of this study are available upon reasonable request. Researchers interested in accessing the data should contact the corresponding author. Furthermore, some data sets used in this study were obtained from Yahoo Finance, Google Mobility Reports, and Data epidemiological sources. The source code and pre-processed data used for this study are publicly available at: https://github.com/Fachrie2019/pandemic-optimization.

6.3. Funding

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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