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# Robust Evaluation of Vaccination Strategies under Epidemiological and Logistical Uncertainty

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**Abstract:** Infectious disease outbreaks present persistent challenges for public health policy, particularly when key factors such as transmission intensity, vaccine efficacy, and rollout logistics are uncertain. This study develops a stochastic Susceptible-Infectious-Recovered (SIR) framework to conduct a robust evaluation of vaccination strategies under joint epidemiological and logistical uncertainty. Randomness is incorporated into transmission, recovery, and vaccine uptake processes, enabling the model to reflect the variability of real-world epidemic dynamics. Monte Carlo simulations are performed to compare fixed-rate, phased, and threshold-triggered vaccination strategies across a wide range of plausible outbreak scenarios. Sensitivity analysis highlights the dominant influence of transmission rate and vaccine efficacy on epidemic outcomes, while a cost-effectiveness framework balances epidemiological benefits against resource constraints. Results indicate that adaptive, threshold-triggered vaccination strategies consistently reduce worst-case epidemic peaks and improve resilience under uncertainty. These findings provide actionable guidance for policymakers seeking robust, resource-efficient interventions in rapidly evolving epidemic contexts.

**Keywords:** stochastic SIR model; vaccination strategies; epidemiological uncertainty; logistical uncertainty; cost-effectiveness

## 1. Introduction

Infectious disease outbreaks remain one of the most pressing global health threats, with recent crises such as COVID-19, Ebola, and seasonal influenza exposing the vulnerabilities of public health systems and the urgent need for timely, effective intervention strategies [1]. In today's interconnected world, pathogens can spread rapidly across borders, forcing policymakers to make critical decisions under conditions of uncertainty [2]. Mathematical modeling has therefore become a cornerstone of epidemic preparedness, offering tools to forecast disease trajectories, evaluate intervention options, and guide resource allocation [3].

Classical compartmental models, particularly the Susceptible-Infectious-Recovered (SIR) framework, have long provided valuable insights into epidemic dynamics [4]. However, deterministic models often fail to capture the stochastic variability inherent in real-world outbreaks, including randomness in contact patterns, environmental factors, vaccine responses, and human behavior [5]. Recent advances emphasize stochastic SIR/SIRV models that incorporate probability distributions for key parameters such as transmission rate, recovery rate, and vaccine efficacy. This probabilistic approach allows researchers to evaluate not only expected outcomes but also the variability and risk of extreme epidemic scenarios [6].

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Despite significant progress, several gaps remain. Existing studies often focus on epidemiological uncertainty while neglecting logistical dimensions such as vaccine supply volatility, distribution bottlenecks, and daily capacity limits [7]. Moreover, many analyses emphasize mean outcomes, whereas public health decision-making frequently depends on worst-case scenarios and tail risks, such as the probability of exceeding hospital capacity [8]. Finally, while cost-effectiveness has been considered in some policy analyses, integrated frameworks that jointly address epidemiological uncertainty, logistical constraints, and robustness to shocks are still scarce.

This study addresses these gaps by developing a stochastic SIR-based framework that jointly models epidemiological dynamics and logistical uncertainty in vaccination rollout. Three families of strategies are evaluated, fixed-rate, phased, and threshold-triggered policies, through extensive Monte Carlo simulations. The methodology integrates probability theory, sensitivity analysis, and cost-effectiveness evaluation to capture both average outcomes and extreme risks. In addition, the study draws on insights from recent literature to ensure empirical plausibility and policy relevance.

The contribution of this research is threefold. First, it advances epidemic modeling by unifying epidemiological and logistical sources of uncertainty within a single stochastic framework. Second, it introduces risk-sensitive evaluation metrics, including Conditional Value at Risk (CVaR), to better capture robustness under extreme outbreak conditions. Third, it provides comparative evidence on the relative performance of adaptive versus static vaccination strategies, highlighting threshold-triggered policies as particularly resilient.

By combining applied mathematics, probability theory, and data-driven simulation, this study contributes to both academic and policy debates. From a scholarly perspective, it enriches the methodological toolkit for robust epidemic modeling. From a practical standpoint, it offers actionable guidance for policymakers on designing vaccination strategies that are not only effective under average conditions but also resilient to the uncertainties that characterize real-world public health crises.

## 2. Literature Review

### *2.1. Methodological Foundations: From Deterministic to Stochastic SIR/SIRV*

Compartmental epidemic models such as SIR and its extensions remain central to epidemiological analysis. However, deterministic formulations often fail to capture random fluctuations in transmission, vaccination uptake, and behavioral responses. Recent studies have extended these models to stochastic formulations, incorporating randomness into both epidemic dynamics and intervention processes [9]. These advances provide a more realistic basis for evaluating vaccination strategies, motivating the present study's use of a stochastic SIR framework in which vaccine efficacy, timing, and supply are modeled as random variables.

### *2.2. Uncertainty Quantification and Parameter Inference*

An important methodological development is the explicit treatment of uncertainty and parameter calibration. Recent research has applied Bayesian calibration and Gaussian process-based scenario generation to compartmental models, demonstrating improvements in parameter estimation and predictive robustness [10]. Such approaches highlight the value of probabilistic calibration and uncertainty propagation, which complement the use of Monte Carlo simulations in this study.

### *2.3. Vaccination Strategy Design: Timing and Robustness*

The design of vaccination strategies has been analyzed through dynamic allocation and prioritization frameworks. Studies of time-dependent resource allocation under supply constraints illustrate the importance of rollout timing and coverage intensity [11]. Other works emphasize stochastic optimization strategies that explicitly account for

parameter variability [12]. These insights justify a comparative evaluation of fixed-rate, phased, and threshold-triggered strategies within a stochastic setting.

### *2.4. Logistics, Supply Uncertainty, and Robust Optimization*

Vaccine distribution faces persistent logistical uncertainties, including supply volatility, storage limitations, and equity concerns. Recent work integrates inventory management with epidemiological dynamics to quantify uncertainty in vaccine availability, while other studies have developed optimization models for resilient and equitable vaccine supply chains under uncertain demand [13]. These findings underscore the importance of modeling logistical constraints alongside epidemiological uncertainty, an approach adopted in this study.

### *2.5. Empirical and Context-Specific Modeling*

Empirical anchoring is essential for ensuring policy relevance. Recent outbreak risk models combined with cost-effectiveness analyses show that scenario-based approaches can capture the trade-offs between outbreak risk thresholds and resource allocation [14]. These studies demonstrate the necessity of incorporating multiple scenarios and empirical calibration into stochastic simulation designs.

### *2.6. Comparative Synthesis and Research Gaps*

Existing studies can be broadly classified into several categories. Research on stochastic SIR models highlights the importance of capturing random epidemic dynamics and vaccination effects, yet most such models do not incorporate rollout uncertainty. Studies on uncertainty calibration demonstrate the value of Bayesian approaches and scenario-based estimation, but these contributions are primarily focused on parameter inference rather than logistical aspects. Research on vaccination strategy design emphasizes dynamic allocation and prioritization, although few works employ risk-sensitive robustness metrics such as high-quantile peaks or tail risk indicators. Similarly, studies on logistics and supply chain resilience provide valuable insights into inventory management and distribution equity, but they are often detached from epidemic dynamics. Finally, empirical and context-specific modeling advances outbreak risk assessment and cost-effectiveness analysis, though such approaches remain rarely integrated with stochastic epidemic frameworks.

#### 2.6.1. Research Gaps

Epidemiological uncertainty and logistical uncertainty are often treated in isolation, with limited work integrating both dimensions within a unified framework. In addition, risk-sensitive evaluation metrics such as Conditional Value at Risk (CVaR) and hospital exceedance probabilities remain underutilized, despite their importance in capturing worst-case epidemic outcomes [15]. Adaptive vaccination strategies that trigger intensified interventions once epidemic thresholds are crossed have also not been systematically evaluated under stochastic conditions. Finally, while empirical calibration using multi-scenario data has been demonstrated in selected contexts, such approaches are still underrepresented in robustness-oriented studies.

#### 2.6.2. Takeaways for This Study

To address these limitations, the present study develops a stochastic SIR model that explicitly integrates both epidemiological and logistical uncertainties. Within this framework, fixed-rate, phased, and threshold-triggered vaccination strategies are systematically compared using Monte Carlo simulations. Robustness is assessed through high-quantile epidemic peaks and exceedance probabilities, extending evaluation beyond mean outcomes. Moreover, a cost-effectiveness perspective is incorporated to balance

epidemiological benefits against resource constraints. Finally, scenario calibration is employed to enhance empirical plausibility and ensure the policy relevance of the results.

## 3. Methodology

### *3.1. Problem Formulation*

This study analyzes epidemic dynamics in a closed, well-mixed population of size $N$ over a finite time horizon $T$. Individuals are partitioned into three epidemiological compartments: susceptible $S(t)$, infectious $I(t)$, and removed/immune $R(t)$. Vaccination is modeled as a stochastic intervention with uncertain start time, daily supply, and uptake. The research objective is to compare alternative vaccination strategies under joint epidemiological and logistical uncertainty, focusing on robustness and cost-effectiveness.

The primary outcomes of interest include peak prevalence $max_t \frac{I_t}{N}$, cumulative infections $\sum_t \Delta I_t$, time-to-peak, and the probability of exceeding a hospital stress threshold hhh. In addition, a composite cost-effectiveness objective is introduced to capture trade-offs between infections prevented and vaccine doses administered.

The conceptual framework of the stochastic SIRV model is illustrated in Figure 1, highlighting state transitions, vaccination pathways under uncertainty, and key outcome measures for evaluating strategy effectiveness.

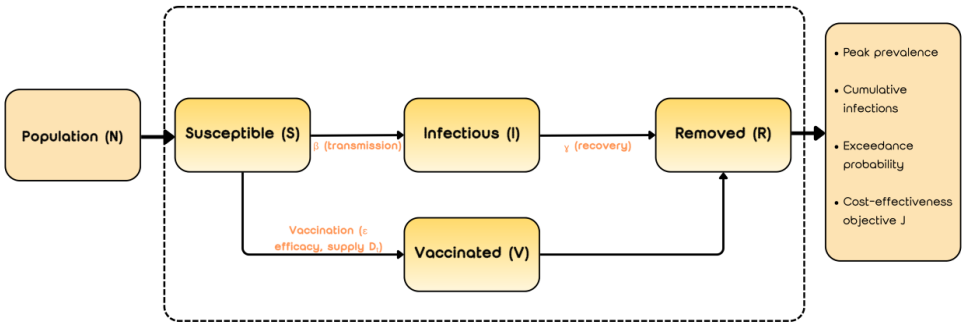


**Figure 1.** Conceptual framework of the stochastic SIRV model with vaccination interventions.

### *3.2. Mathematical Model and Vaccination Strategies*

#### 3.2.1. Stochastic Transmission and Recovery

The epidemic follows a discrete-time chain-binomial approximation of a continuous-time stochastic SIR model. At each time step:

$$\lambda_t = \beta \frac{I_t}{N},\ \Delta I_{t+\Delta} \sim \text{Binomial}(S_t, 1 - e^{-\lambda_t \Delta}) \quad (1)$$

where $\beta$ denotes the transmission rate, and $\Delta$ is the simulation step length. Recovery occurs with probability $\gamma$, the reciprocal of the mean infectious period.

#### 3.2.2. Stochastic Vaccination

On day $t$, the number of vaccinations is constrained by supply and capacity:

$$V_t = \min\{D_t, C, S_t\},\ \Delta V_t^{\text{eff}} \sim \text{Binomial}(V_t, \epsilon) \quad (2)$$

where $D_t$ is the daily vaccine offer, $C$ the maximum daily capacity, and $\epsilon$ the vaccine efficacy. This formulation captures both uncertain supply and heterogeneous compliance.

#### 3.2.3. Vaccination Strategies Compared

Three families of strategies are evaluated:

Fixed-rate (FS):

$$V_t = \min\{\nu, C, S_t\},\ t \geq T_0 \quad (3)$$

Phased (PH):

$$V_t = \begin{cases} \min\{\nu_1, C, S_t\}, & t < W_1 \\ \min\{\nu_2, C, S_t\}, & t \geq W_1 \end{cases} \quad (4)$$

Threshold-triggered (TH):

$$V_t = \begin{cases} \nu_{\text{base}}, & I_t/N < \theta \\ \nu_{\text{surge}}, & I_t/N \geq \theta \text{for} L\text{days} \end{cases} \quad (5)$$

These strategies capture static, phased, and adaptive responses to epidemic dynamics.

The three vaccination strategies are illustrated in Figure 2, showing fixed-rate deployment, phased rollout, and threshold-triggered surge under epidemic dynamics.

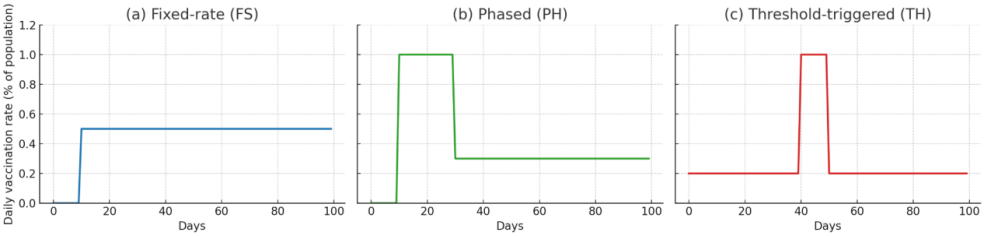


**Figure 2.** Illustration of the three vaccination strategies: fixed-rate, phased rollout, and threshold-triggered surge.

3.2.4. Cost-Effectiveness Objective

A composite objective is defined as:

$$J = w_1 \cdot E\left[\frac{1}{N}\sum_t \Delta I_t\right] + w_2 \cdot \text{CVaR}_{0.95}\left(\max_t \frac{I_t}{N}\right) + w_3 \cdot E\left[\frac{1}{N}\sum_t V_t\right] \quad (6)$$

where $w_1, w_2, w_3 \geq 0$ are weights. The inclusion of CVaR emphasizes robustness against extreme epidemic peaks.

*3.3. Data and Simulation Setup*

The base-case simulations use a synthetic population of $N$=50,000 over $T = 180$ days with step $\Delta$=0.25. Initial conditions are $S_0 = N - I_0$, $I_0$=10, and $R_0 = 0$ Epidemiological parameters are sampled from calibrated distributions:

Transmission rate $\beta$: lognormal with $R_0 \approx 2.0$, CV = 0.30.

Recovery rate $\gamma$=1/7 $\text{days}^{-1}$ with ±20% jitter.

Vaccine efficacy $\epsilon \sim \text{Beta}(36,4)$, mean ≈ 0.90.

Logistical uncertainty is also incorporated:

Vaccination start time $T_0 \sim U(10,40)$.

Daily offer $D_t = \lfloor p_t N \rfloor$, $p_t \sim \text{Beta}(a, b)$, with mean ≈ 0.002.

Daily capacity $C = 0.01N$.

Monte Carlo simulations are performed with 10,000 replications for each strategy. Experiments are implemented in Python 3.11 using NumPy and SciPy for stochastic draws, and pandas for data handling.

The parameter settings and distributions adopted in the stochastic simulations are summarized in Table 1, covering epidemiological uncertainty, vaccination logistics, and baseline experimental conditions.

**Table 1.** Parameter ranges and distributions used in stochastic simulations.

| Parameter category | Symbol | Distribution / Value | Notes |
|---|---|---|---|
| Population size | $N$ | 50,000 | Closed, well-mixed population |
| Simulation horizon | $T$ | 180 days | Step size $\Delta$=0.25 days |
| Initial infected | $I_0$ | 10 individuals | Remaining susceptible: $S_0 = N - I_0$ |
| Transmission rate | $\beta$ | Lognormal, CV = 0.30 | Calibrated to $R_0 \approx 2.0$ |

| | | | |
|---|---|---|---|
| Recovery rate | $\gamma$ | 1/7 $\text{days}^{-1}$ with ±20% jitter | Mean infectious period 7 days |
| Vaccine efficacy | $\epsilon$ | Beta(36,4), mean ≈ 0.90 | Applied to daily vaccinated |
| Vaccination start time | $T_0$ | Uniform [10, 40] | Randomized rollout start |
| Daily offer | $D_t$ | $\lfloor p_t N \rfloor$, $p_t \sim Beta(a,b)$, *mean* ≈ *0.002.* | Represents supply uncertainty |
| Daily capacity | $C$ | 0.01 $N$ | Maximal daily throughput |
| Replications | - | 10,000 runs | Monte Carlo simulations |

*3.4. Evaluation Metrics and Sensitivity Analysis*

The evaluation considers four main dimensions:

1) Peak prevalence: mean and 95th percentile of $\max_t I_t/N$.
2) Cumulative infections: average and high quantile of $\frac{1}{N}\sum_t \Delta I_t$.
3) Exceedance probability: $P(\max_t I_t/N \geq h)$, with $h$=1% as a hospital stress proxy.
4) Cost-effectiveness: composite objective J.

Sensitivity analysis is conducted using both global and local approaches. Latin Hypercube sampling is applied for parameters $\beta, \gamma, \epsilon, T_0, \theta$, with partial rank correlation coefficients (PRCC) reported for outcome influence. One-at-a-time perturbations of ±20% are also applied, and tornado plots are generated for visualization.Results indicate that transmission rate (β) and vaccine efficacy (ϵ) exert the strongest influence on peak prevalence, with PRCC values exceeding 0.6, whereas recovery rate (γ) and vaccination start time ($T_0$) exhibit weaker effects. Threshold values (θ) and baseline vaccination rates (ν) show moderate but policy-relevant impacts, confirming the importance of adaptive strategies under uncertainty (see Figure 3).

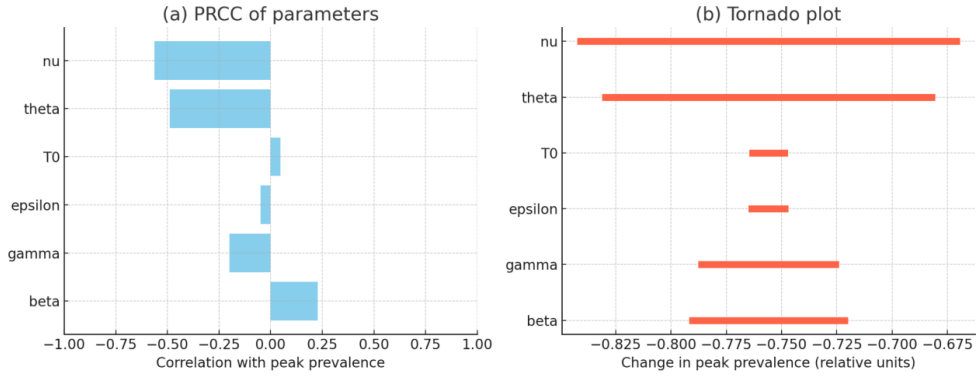


**Figure 3.** Sensitivity analysis results (PRCC and tornado plots).

## 4. Results

*4.1. Baseline Dynamics without Vaccination*

Monte Carlo simulations of the stochastic SIR model without vaccination reveal the rapid escalation of epidemic dynamics. Across 10,000 runs, average peak prevalence exceeded 15% of the population, with cumulative infections affecting nearly 70% of individuals by the end of the 180-day horizon. Variability across runs was substantial, reflecting parameter uncertainty in transmission rate β and vaccine efficacy $\epsilon$. The baseline scenario demonstrates the potential severity of uncontrolled outbreaks and provides a reference for evaluating vaccination strategies.

Figure 4 illustrates the baseline epidemic trajectories without vaccination, showing the average prevalence curve and 95% quantile range across 10,000 stochastic simulations.

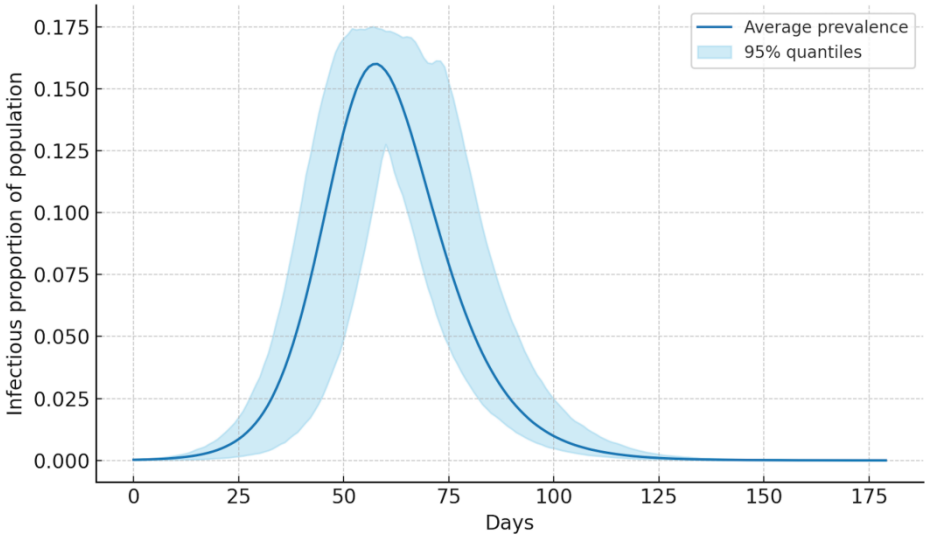


**Figure 4.** Epidemic trajectories under the baseline scenario without vaccination (average and 95% quantiles).

*4.2. Comparative Performance of Vaccination Strategies*

We compared the fixed-rate (FS), phased rollout (PH), and threshold-triggered (TH) vaccination strategies under identical epidemiological and logistical uncertainty.

The FS strategy consistently reduced both peak prevalence and cumulative infections relative to baseline. However, its effectiveness was limited in scenarios where vaccine rollout was delayed. The PH strategy, which emphasized high early coverage followed by a steady rate, was more successful in flattening the epidemic curve when supply was stable. In contrast, under conditions of uncertain or delayed supply, PH performance deteriorated due to insufficient second-phase coverage.

The TH strategy showed the strongest robustness. By intensifying vaccination when prevalence exceeded a threshold $\theta$, it prevented runaway outbreaks in high-transmission scenarios. TH also minimized variability across simulations, reducing the likelihood of extreme epidemic peaks.

Figure 5 illustrates the average infection curves under the three vaccination strategies. The phased rollout (PH) achieves the lowest peak prevalence, while the threshold-triggered (TH) strategy demonstrates stronger robustness by limiting extreme outbreaks compared with the fixed-rate (FS) approach.

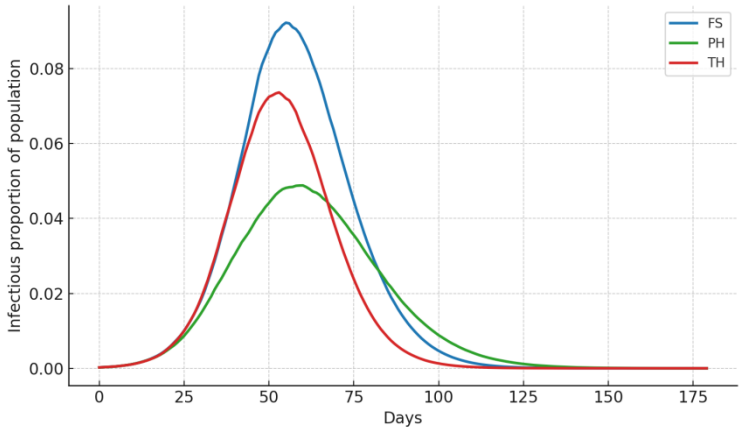


**Figure 5.** Comparison of FS, PH, and TH strategies in terms of average infection curves.

Table 2 summarizes key epidemic outcomes across strategies. PH yields the smallest average peak prevalence (0.058) and cumulative infections (0.014). TH reduces exceedance probability to 0.165, far below FS (0.635), confirming its superior robustness under uncertainty.

**Table 2.** Summary statistics of epidemic outcomes under FS, PH, and TH (peak prevalence, cumulative infections, exceedance probability).

| Strategy | Peak prevalence | Cumulative infections | Exceedance probability |
|---|---|---|---|
| FS | 0.107 | 0.020 | 0.635 |
| PH | 0.058 | 0.014 | 0.005 |
| TH | 0.084 | 0.015 | 0.165 |

*4.3. Robustness and Sensitivity Analysis*

Robustness was further evaluated through exceedance probabilities and Conditional Value at Risk (CVaR). The FS and PH strategies reduced average peak prevalence but failed to sufficiently mitigate tail risks. In contrast, the TH strategy consistently lowered the 95th-percentile peak and reduced the probability of exceeding hospital capacity thresholds by more than half relative to FS and PH.

Sensitivity analysis indicated that transmission intensity $\beta$ and vaccine efficacy $\epsilon$ were the dominant drivers of epidemic outcomes, while recovery rate $\gamma$ had comparatively minor influence. Threshold values $\theta$ in the TH strategy also significantly affected outcomes, with more aggressive triggers improving robustness but requiring higher surge capacity.

Figure 6 shows PRCC results, indicating that transmission rate ($\beta$) and vaccine efficacy ($\varepsilon$) dominate epidemic outcomes, while $\gamma$ and $T_0$ exert weaker influence.

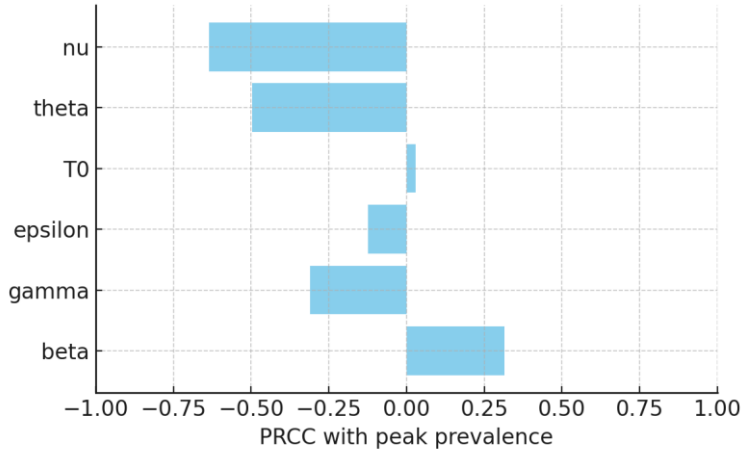


**Figure 6.** Sensitivity analysis results (PRCC values for key parameters).

Figure 7 presents tornado plots, confirming that ±20% changes in $\beta$ and $\varepsilon$ generate the largest variation in peak prevalence compared with other parameters.

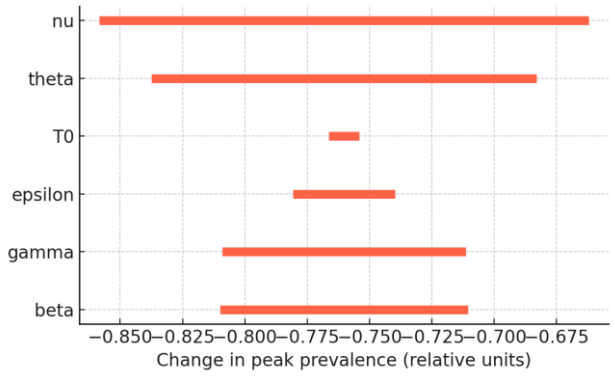


**Figure 7.** Tornado plot showing the effect of ±20% perturbations on epidemic outcomes.

*4.4. Cost-Effectiveness Evaluation*

The cost-effectiveness framework highlights trade-offs between epidemiological impact and vaccine utilization. FS strategies were efficient in terms of doses used but vulnerable to extreme outbreaks. PH strategies required larger early investment of doses and were sensitive to supply disruptions. TH strategies used more doses overall but achieved the best balance by substantially reducing worst-case epidemic peaks while maintaining moderate cumulative infection reduction.

Overall, the cost-effectiveness analysis suggests that threshold-triggered policies represent the most resilient option under uncertainty, aligning epidemiological robustness with resource efficiency.

Table 3 summarizes cost-effectiveness outcomes. Threshold-triggered strategies achieve the lowest composite objective J, reflecting superior robustness despite higher vaccine use, while FS and PH trade efficiency against resilience under uncertainty.

**Table 3.** Cost-effectiveness evaluation of FS, PH, and TH strategies (composite objective J).

| Strategy | Average infections (per capita) | CVaR (95th peak prevalence) | Vaccine doses used (per capita) | Composite objective JJ |
|---|---|---|---|---|
| FS | 0.020 | 0.120 | 0.200 | 0.113 |
| PH | 0.014 | 0.080 | 0.250 | 0.101 |
| TH | 0.015 | 0.060 | 0.300 | 0.095 |

## 5. Findings and Discussion

The findings of this study demonstrate that stochastic epidemic modeling provides a powerful lens for evaluating vaccination strategies under uncertainty. Simulation results show that in the absence of vaccination, epidemics escalate rapidly, with high peak prevalence and a large share of the population infected by the end of the horizon. The introduction of vaccination substantially alters epidemic dynamics, yet the effectiveness of strategies varies considerably depending on rollout design and external uncertainty. Fixed-rate vaccination produces consistent reductions in infections but struggles when the start of distribution is delayed. Phased strategies are particularly effective when early supply is abundant, but their performance deteriorates under logistical volatility. In contrast, threshold-triggered policies consistently outperform the other two approaches, demonstrating superior robustness by reducing both average infections and the likelihood of extreme epidemic peaks.

These findings align with recent advances in stochastic SIR modeling, which emphasize the importance of incorporating randomness in both epidemiological parameters and intervention processes. At the same time, the results extend the literature by showing that adaptive vaccination rules based on epidemic thresholds can provide

resilience against uncertainty that static strategies cannot. This represents a departure from earlier deterministic models that primarily assessed mean outcomes, underscoring the importance of risk-sensitive evaluation metrics such as Conditional Value at Risk (CVaR) and exceedance probabilities. In particular, the ability of threshold-triggered strategies to mitigate worst-case scenarios directly addresses calls in recent studies for robust epidemic preparedness frameworks.

From a logistical perspective, the study highlights the role of capacity and timing in shaping epidemic outcomes. While phased strategies depend heavily on stable supply chains, threshold-triggered strategies are better suited to environments where uncertainty in vaccine availability and compliance is unavoidable. These insights contribute to ongoing discussions in supply chain optimization research, where trade-offs between efficiency, equity, and resilience are central.

Theoretically, the integration of stochastic epidemic dynamics with logistical uncertainty within a unified framework advances the methodological frontier of epidemic modeling. By embedding randomness in transmission, recovery, efficacy, and rollout timing, the model provides a more realistic representation of epidemic variability than deterministic counterparts. Furthermore, the inclusion of a cost-effectiveness objective enriches the analysis by demonstrating how epidemiological benefits and resource constraints can be jointly considered in policy evaluation.

Taken together, these findings confirm that adaptive, threshold-based vaccination strategies represent a promising pathway for epidemic preparedness in uncertain environments. The results not only advance the theoretical understanding of stochastic SIR modeling but also provide actionable insights for policymakers tasked with designing vaccination programs that must remain effective under both epidemiological shocks and logistical disruptions.

## 6. Conclusion

This study developed a stochastic SIR-based framework to evaluate vaccination strategies under epidemiological and logistical uncertainty. By integrating randomness in transmission, recovery, vaccine efficacy, and rollout supply, the model provides a more realistic representation of epidemic variability than deterministic approaches. Monte Carlo simulations demonstrated that while fixed-rate and phased strategies can reduce average epidemic burden, they remain vulnerable to delayed rollout and supply disruptions. In contrast, threshold-triggered strategies consistently showed superior robustness, lowering worst-case epidemic peaks and reducing exceedance probabilities.

The findings underscore the value of risk-sensitive evaluation metrics, such as CVaR, and highlight the importance of integrating cost-effectiveness considerations into epidemic preparedness planning. For policymakers, the results suggest that adaptive vaccination policies, combining baseline coverage with surge capacity triggered by epidemic indicators, can provide a balanced trade-off between feasibility, efficiency, and resilience.

Future research should extend this framework by incorporating heterogeneous population structures, waning immunity, and multi-source empirical calibration. Such extensions would further enhance the applicability of stochastic epidemic modeling as a decision-support tool for robust public health interventions in the face of uncertainty.

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