Faculty of Natural and Applied Sciences Journal of Applied Biological Sciences
Print ISSN: 3027-0685, e-ISSN: 3043-6494
www.fnasjournals.com
Volume 2; Issue 4; December 2025; Page No. 36-43.
DOI: https://doi.org/10.63561/jabs.v2i4.1006

AI-Enhanced SEIR Modelling for Adaptive Control of Diphtheria Outbreaks in Delta State, Nigeria

[*1]Evuiroro, E.J., & [2]Okwonu, F.Z.
[1,2] Department of Mathematics, Delta State University, Abraka, Delta State, Nigeria.

***Corresponding author email:** judy4edirin@gmail.com

Abstract
Mathematical models like the Susceptible-Exposed-Infectious-Recovered (SEIR) framework are vital for epidemic control but are often limited by static parameters in dynamic settings. This study develops a hybrid framework that integrates Pontryagin's Maximum Principle for optimal control with artificial intelligence (AI) components—including Long Short-Term Memory (LSTM) networks for forecasting and a Genetic Algorithm (GA) for real-time parameter adaptation—to transform a traditional SEIR model into an adaptive decision-support system. Applied to diphtheria outbreak management as a case study in Delta State, Nigeria, the AI-augmented model was evaluated using synthetic data derived from Nigeria Centre for Disease Control parameters. It reduced forecast error by 80% (MAPE: 4.6% vs. 22.8%), peak infections by 66.5%, and improved intervention cost-efficiency compared to the optimized control-only model. The findings suggest that AI-mechanistic modelling provides a scalable methodological framework for precision public health, especially in resource-limited settings, through improvements in predictive performance, resiliency, and cost-effectiveness.

Keywords: Artificial Intelligence, Hybrid Epidemiological Modelling, Optimal Control, Diphtheria, SEIR Model.

Introduction
Infectious diseases continue to present challenges for public health systems, especially in low-resource contexts, such as Nigeria. In Delta State, there have been a number of repeated outbreaks of diphtheria, cholera and Lassa fever (NCDC, 2023). While mathematical modelling has provided a basis of research to describe the epidemic dynamics, evaluate the impact of options for intervention and assist with guidance on policy, they have been used for some time. Compartmental models have become a common approach, such as the Susceptible– Exposed–Infectious–Recovered (SEIR) model, due to interpretations and biological rationale (Brauer, 2017). The basic reproduction number R_0 serves as a critical threshold parameter in such models, determining whether a disease will spread or die out in a population (Van den Driessche & Watmough, 2002). Traditional methods of applying SEIR present significant limitations, primarily for two reasons: parameters are often fixed or estimated from historical data; and optimal control strategies derived from Pontryagin's Maximum Principle act as open-loop systems. Therefore, when abrupt changes occur in the real world, such as during population mobility, intervention fatigue, or pathogen change, the models have no way of adjusting. AI methods, including machine and deep learning, offer new opportunities to overcome these shortcomings. AI methods are inductive and data-driven, capable of detecting nonlinear relationships across diverse variables such as clinical, demographic, and mobility data (Alotaibi et al., 2023). Recurrent neural networks, notably Long Short-Term Memory (LSTM) architectures, have achieved strong performance in epidemic forecasting (Chae et al., 2021). Likewise, heuristic optimization techniques, like Genetic Algorithms (GA), have been used in epidemiology to estimate parameters and optimize nonlinearity (Arduino, 2021). While the potential of such methods is novel, data-driven models generally provide a "black box" for interpreting processes in public health.

Recent work also showcases the possibilities of hybrid models that combine mechanistic approaches with AI approaches, offering the interpretability of compartmental models and utilizing AI for adaptive parameter estimation to improve forecast accuracy (Willcox et al., 2021; Lu et al., 2023; Kumar & Susan, 2024). Despite promising research, nearly all studies have assumed sufficient strong datasets and surveillance systems which are uncommon in low- and middle-income countries. In addition, there have been few attempts to statistically

quantify the degree to which predictive accuracy, adaptability, and cost-effectiveness improve by using AI-optimized parameters within the control-optimized SEIR model, while working under resource constraints.
This study addresses these gaps by developing and evaluating a hybrid SEIR–AI framework for modelling diphtheria outbreaks in Delta State, Nigeria. Delta State is a particularly relevant case study based on its recurring history of diphtheria outbreaks, a formal setting which captures its diverse urban and rural populations, and health system components which are common in heavily resource-constrained environments across Nigeria and Sudan. The knowledge obtained in this context will provide evidence of an expandable framework applicable to like regions. Specifically, our contributions are threefold:

- We formulate a control-extended SEIR model with vaccination and treatment strategies optimized using Pontryagin's Maximum Principle.
- We design an AI augmentation layer consisting of (i) an LSTM network for short-term forecasting, (ii) a GA for real-time, time-varying parameter estimation, and (iii) neural network–based sensitivity analysis for policy prioritization.
- We provide a comparative evaluation against baseline and control-only SEIR model, demonstrating significant improvements in forecast accuracy, outbreak mitigation, and intervention cost-efficiency.

Compartmental models have long provided the foundation for mathematical epidemiology. Frameworks such as the Susceptible–Exposed–Infectious–Recovered (SEIR) model, which first developed as modelling approaches by Kermack and McKendrick, remain popular for their intuitive appeal and ability to recover important features of transmission dynamics (Brauer, 2017). SEIR-type compartments have been used in Nigeria to consider diphtheria and provide evidence for outbreak readiness and intervention preparation (Ayansiji & Ejinkonye, 2025). While these modelling approaches may be useful, they usually rely on fixed values of parameters based on past data and do not incorporate important factors in a changing environment such as mobility or changing effectiveness of intervention, or responses by the pathogens.

To address these limitations, optimal control theory offers a method of extending compartmental models, by incorporating vaccination, treatment, or isolation into dynamic models. Pontryagin's Maximum Principle, in particular, provides a rigorous mathematical method for balancing infection reduction with economic costs (Naidu, 2003). Matrajt et al. (2021) showed that vaccine allocation strategies significantly affect epidemic outcomes, while Bliman et al. (2021) demonstrated how control theory can optimize epidemic suppression through social distancing. However, most existing solutions remain open-loop, optimized at the start of an outbreak and applied unchanged throughout its course.

Simultaneously, Artificial Intelligence (AI) has surfaced as a revolutionary instrument for epidemiology. Methods in machine learning and deep learning inductively acquire knowledge from data rather than pre-specified hypotheses, successfully detecting nonlinear associations across multiple domains (e.g., clinical records, mobility data, environmental parameters) (Jiang et al., 2017). Models such as recurrent neural networks - including Long ShortTerm Memory (LSTM) architectures - have reached state-of-the-art accuracies for forecasting epidemics such as influenza and COVID-19 (Chae et al., 2021). Evolutionary algorithms (such as Genetic Algorithms [GAs]) have become functional methods for estimating parameters and nonlinear optimization and estimation in epidemiological models (Arduino, 2021). Recent advances in metaheuristic optimization, such as the Enhanced Grey Wolf Optimizer with chaotic initialization and adaptive control (Ayansiji et al., 2025), have demonstrated improved convergence and robustness in complex search spaces, suggesting potential utility in epidemiological parameter calibration. Yet, these purely data-driven models are often criticized as opaque "black boxes," which limits their acceptance in policymaking contexts where interpretability is essential.

An emerging frontier is the integration of mechanistic and AI-driven approaches into hybrid frameworks. These models aim to combine the interpretability of compartmental structures with the adaptability of AI techniques. For instance, Lu et al. (2023) incorporated regression and heuristic methods into an SEIR model to capture wave-specific dynamics during COVID-19 in Italy, obtaining more accurate predictions. Kumar and Susan (2024) developed a time varying SIRD model enhanced with Particle Swarm Optimization and stacked LSTM networks to generate robust forecasts for multiple waves. Other studies have advanced graph-based approaches, such as Metapopulation Graph Neural Networks, which incorporate mobility data into mechanistic models while preserving biological meaning.

Taken together, the literature reveals two largely parallel traditions: mechanistic SEIR model that are interpretable but static, and AI-driven approaches that are adaptive but less transparent. Although hybrid models have begun to bridge these traditions, most existing work assumes abundant high-quality data and robust surveillance systems. Few studies rigorously quantify the benefits of AI integration when embedded within optimal control models under resource constrained conditions. This gap leaves policymakers with either static tools that quickly lose relevance or adaptive systems that lack interpretability. The present study addresses this challenge by proposing and evaluating a hybrid AI–SEIR framework tailored to diphtheria outbreak control in Delta State, Nigeria, with the aim of transforming static modelling tools into adaptive, predictive, and prescriptive decision-support systems.

Aim and Objectives

The primary aim of this study is to develop and validate a hybrid AI-mechanistic framework for the adaptive control of diphtheria outbreaks in resource-limited settings. To achieve this aim, the following specific objectives were pursued to:

1. formulate a control-extended SEIR model with vaccination and treatment strategies optimized using Pontryagin's Maximum Principle.
2. design an AI augmentation layer consisting of an LSTM network for forecasting, a GA for real-time parameter estimation, and a neural network for sensitivity analysis.
3. conduct a comparative evaluation of the proposed AI-augmented model against baseline and control-only models, assessing improvements in forecast accuracy, outbreak mitigation, and cost-efficiency.

Materials and Methods

We design and evaluate a hybrid modelling framework to simulate diphtheria dynamics within the population of Delta State, Nigeria, under three scenarios:

1. Scenario A (Baseline): classical SEIR model with static parameters.
2. Scenario B (Optimized Control): SEIR model with vaccination and treatment controls derived from Pontryagin's Maximum Principle.

Scenario C (AI-Augmented): control-optimized SEIR model enhanced with AI modules for forecasting, parameter adaptation, and sensitivity analysis.

Model Formulation

Let the total population be

$$N(t) = S(t) + E(t) + I(t) + R(t) \tag{1}$$

where $S(t)$, $E(t)$, $I(t)$, and $R(t)$ denote susceptible, exposed, infectious, and recovered/removed individuals, respectively.

The controlled SEIR dynamics are:

$$\left.\begin{aligned} \frac{dS}{dt} &= \Lambda - \frac{\beta(t)IS}{N} - \mu S - u_1(t)S, \\ \frac{dE}{dt} &= \frac{\beta(t)IS}{N} - (\sigma + \mu)E, \\ \frac{dI}{dt} &= \sigma E - (\gamma + \mu + \delta)I - u_2(t)I, \\ \frac{dR}{dt} &= \gamma I + u_1(t)S + u_2(t)I - \mu R, \end{aligned}\right\} \tag{2}$$

where Λ is the recruitment rate, μ the natural mortality, σ the incubation rate, γ the recovery rate, and δ the disease-induced mortality. Control functions $u_1(t), u_2(t) \epsilon [0, 1]$ represent vaccination and treatment.

Optimal Control Problem Formulation (Scenario B)

To derive the optimal intervention strategies for Scenario B, we define an objective functional J to be minimized. This functional balances the cost of the infected population against the costs of implementing vaccination and treatment programs over a fixed time period [0, T]:

$$J(u_1, u_2) = \int_0^T \left[AI(t) + \frac{B_1}{2}u_1^2(t) + \frac{B_2}{2}u_2^2(t)\right] dt, \tag{3}$$

where:

1 $AI(t)$: Cost associated with the burden of disease (e.g., healthcare costs, productivity loss).
2 $\frac{B_1}{2}u_1^2(t)$: Cost of vaccination implementation, assumed to be non-linear to model diminishing returns and logistical challenges.
3 $\frac{B_2}{2}u_2^2(t)$: Cost of treatment implementation.
4 A, B_1, B_2: Positive weighting constants that translate health and economic outcomes into a common cost framework.

The goal is to find optimal control functions $u_1^*(t)$ and $u_2^*(t)$ such that:

Cite this article as:
Evuiroro, E.J., & Okwonu, F.Z. (2025). AI-Enhanced SEIR Modelling for adaptive control of diphtheria outbreaks in Delta State, Nigeria. *FNAS Journal of Applied Biological Sciences, 2*(4), 36-43. https://doi.org/10.63561/jabs.v2i4.1006

$$J(u_1^*, u_2^*) = \min_{u_1, u_2 \in U} J(u_1, u_2), \quad (4)$$

subject to the state equations above, where U is the set of admissible measurable controls. The admissible control set is defined as

$$U = \{(u_1, u_2): u_i: [0, T] \to [0, 1], i = 1, 2\}. \quad (5)$$

Theorem 1. (Existence of Optimal Control)

Given the bounded, Lipschitz continuous state system (2) and the convex, compact admissible control set U defined in (5), there exists an optimal control pair $u_1, u_2 \in U$ minimizing the cost functional $J(u_1, u_2)$ in (3) over the time interval [0, T].

The proof follows standard results in optimal control theory (Fleming & Rishel, 1975).

Hamiltonian and Adjoint System

We apply Pontryagin's Maximum Principle to solve this. The Hamiltonian H is formed:

$$\begin{aligned} H = AI + \frac{B_1}{2}u_1^2 + \frac{B_2}{2}u_2^2 + \lambda_S\left(\Lambda - \frac{\beta IS}{N} - \mu S - u_1 S\right) + \\ \lambda_E\left(\frac{\beta(t)IS}{N} - (\sigma+\mu)E\right) + \lambda_I(\sigma E - (\gamma+\mu+\delta)I - u_2 I) + \\ \lambda_R(\gamma I + u_1(t)S + u_2(t)I - \mu R). \end{aligned} \quad (6)$$

The adjoint variables λ_i (for $i = S, E, I\ R$) satisfy the following costate equations:

$$\left.\begin{aligned} \frac{d\lambda_S}{dt} = -\frac{\partial H}{\partial S} = \lambda_S\left(\frac{\beta I}{N} + \mu + u_1\right) - \lambda_E\left(\frac{\beta I}{N}\right) - \lambda_R u_1, \\ \frac{d\lambda_E}{dt} = -\frac{\partial H}{\partial E} = \lambda_E(\sigma+\mu) - \lambda_I\sigma, \\ \frac{d\lambda_I}{dt} = -\frac{\partial H}{\partial I} = -A + \lambda_S\left(\frac{\beta S}{N}\right) - \lambda_E\left(\frac{\beta S}{N}\right) + \lambda_I(\gamma+\mu+\delta+u_2) - \lambda_R(\gamma+u_2), \\ \frac{d\lambda_R}{dt} = -\frac{\partial H}{\partial R} = \mu\lambda_R, \end{aligned}\right\} \quad (7)$$

with terminal conditions $\lambda_S(T) = \lambda_E(T) = \lambda_I(T) = \lambda_R(T) = 0$.

Characterization of Optimal Controls

The optimal controls are derived by solving $\frac{\partial H}{\partial u_1} = 0$ and $\frac{\partial H}{\partial u_2} = 0$:

$$\left.\begin{aligned} u_1^*(t) = max\left(0, \min\left(u_1^{max}, \frac{(\lambda_S - \lambda_R)S}{B_1}\right)\right) \\ u_2^*(t) = max\left(0, \min\left(u_2^{max}, \frac{(\lambda_I - \lambda_R)I}{B_2}\right)\right) \end{aligned}\right\} \quad (8)$$

This system of state and costate equations, with boundary conditions (initial states and terminal time conditions for adjoints), was solved numerically using a forward-backward sweep algorithm in MATLAB. The iteration process continued until the relative error between successive iterations for all state and control variables was less than a tolerance of 10^{-5}, ensuring convergence.

AI-Augmentation Framework (Scenario C)

While the optimal control model (Scenario B) provides a theoretically powerful framework, its effectiveness in a real-world outbreak is limited by its reliance on a fixed transmission rate β. LSTM was selected due to its proven ability to handle long-term temporal dependencies in epidemic data. GA was chosen for parameter estimation given its robustness in handling noisy, non-convex optimization problems typical of epidemiological datasets. To create a responsive and adaptive model, we integrated an AI engine designed to dynamically calibrate this critical parameter in real-time.

1. **LSTM Forecasting Module:** A Long Short-Term Memory (LSTM) recurrent neural network was implemented in Python using TensorFlow/Keras. The network, comprising two LSTM layers (50 units each followed by a Dropout layer of 0.2) and a dense output layer, was trained on the historical time series of infectious individuals $I(t)$. Using ReLU activation and the Adam optimizer, it was designed to predict future values $\hat{I}(t+p)$ with a 4-week prediction horizon ($p = 28$), providing a probabilistic early warning signal.
2. **Genetic Algorithm for Dynamic Parameterization:** A Genetic Algorithm (GA) was designed to solve the inverse problem of finding the optimal time-varying transmission rate $\beta(t)$. The GA represented $\beta(t)$as a chromosome of discretized daily values. Its fitness function minimized a weighted

sum of the Mean Squared Error (MSE) between the model output $I_{model}(t)$ and the empirical data $I_{data}(t)$, and the MSE between the model projection and the LSTM forecast values $\hat{I}(t+p)$, That is,

$$\min F(\beta) = \alpha MSE\big(I_{model}(t), I_{data}(t)\big) + (1-\alpha) MSE\left(I_{model}(t), \hat{I}(t+p)\right) \quad (9)$$

We employed a population size of 100, tournament selection, two-point crossover, and an adaptive mutation rate, running for 200 generations to ensure convergence.

3. **AI-Powered Sensitivity Analysis:** A feedforward neural network surrogate model was trained to emulate the input-output relationship of the full SEIR model. This computationally efficient surrogate enabled a rapid global sensitivity analysis using the variance-based Sobol method, quantifying the contribution of each parameter (e.g., β, σ, u_1) to the variance in key outputs (e.g., peak I, total cost), thereby identifying the most critical and influential intervention levers for policymakers.

Hybrid Solver

Algorithm 1: AI-Augmented Optimal Control Solver

Input: Initial states (S_0, E_0, I_0, R_0), parameters, NCDC/synthetic data

Initialize $\beta(t)$, controls u1(t), u2(t)

Repeat until convergence:

1. Solve SEIR forward in time (Runge–Kutta 4).
2. Solve adjoint system backward in time.
3. Update controls using characterization formulas.
4. LSTM forecasts incidence $\tilde{I}(t+p)$.
5. GA updates $\beta(t)$ using fitness function F(β).
6. Surrogate N performs sensitivity analysis.

Output: Optimal controls $u_1^*(t)$, $u_2^*(t)$, state trajectories

Numerical Simulation and Performance Evaluation

Model parameters were primarily calibrated using demographic data from the National Bureau of Statistics (2022) for Delta State and epidemiological data from NCDC surveillance reports specific to the region. To compensate for gaps in high-resolution, real-time data—a common challenge in such settings—synthetic datasets were generated based on these established parameters and ranges reported in the literature for similar diphtheria outbreaks. This approach allows for the robust validation of the modelling framework's functionality, with the primary objective being a comparative analysis of the scenarios rather than precise real-world prediction at this stage.

The coupled system of ODEs was solved numerically using a fourth-order Runge-Kutta method. The performance of Scenarios A, B, and C was evaluated and compared based on the following metrics:

1.0 Predictive Accuracy: Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE).

2.0 Epidemic Control: Peak infection rate, total cases averted, total deaths averted.

3.0 Economic Efficiency: Total cost of intervention strategies $J(u_1, u_2)$.

4.0 Adaptability: Model response time and accuracy after a simulated sudden increase in transmission rate (β).

Results

This section presents the outcomes of the three scenarios outlined in Section 3. Numerical experiments were conducted in MATLAB using the forward–backward sweep algorithm for the optimal control system and the AI modules for adaptive forecasting and parameter adjustment. A fourth-order Runge–Kutta solver with step size 0.01 was used. Model parameters were calibrated from demographic data and NCDC surveillance reports, supplemented with synthetic data where necessary.

Baseline Dynamics (Scenario A)

The baseline SEIR model reproduces the natural progression of diphtheria in a closed population. Infections rise sharply, peaking earlier and at higher magnitude than observed NCDC reports. This deviation illustrates the limitations of static-parameter models in situations of dynamism such as Delta State, where heterogeneous contact rates vary as a result of seasonal effects, movement, and localized disruption from interventions. The uncontrolled epidemic estimated a peak prevalence of 18.5% of the population, leading to cumulative incidence and mortality figures that vastly exceed historically observed outbreaks, highlighting its lack of real-world applicability without intervention.

Cite this article as:
Evuiroro, E.J., & Okwonu, F.Z. (2025). AI-Enhanced SEIR Modelling for adaptive control of diphtheria outbreaks in Delta State, Nigeria. *FNAS Journal of Applied Biological Sciences, 2*(4), 36-43. https://doi.org/10.63561/jabs.v2i4.1006

Optimal Control Dynamics (Scenario B)
Introducing vaccination and treatment controls significantly alters epidemic trajectories. The forward–backward sweep algorithm converged within 30 iterations, achieving a tolerance 10^{-5}. Vaccination control $u_1(t)$ is high during the early phase, suppressing initial spread, while treatment control $u_2(t)$ peaks around the infection apex, reflecting the need for targeted therapeutic interventions.

Table 1 :Comparative epidemic outcomes for the baseline SEIR model (Scenario A) and the model with optimal control interventions (Scenario B). The percentage reduction demonstrates the significant impact of optimizing vaccination and treatment strategies.

Indicator	Scenario A (Baseline)	Scenario B (Control)	% Reduction
Peak infection proportion (%)	18.5	9.7	47.6
Total cases per 100,000	2,450	1,230	49.8
Total deaths per 100,000	375	195	48.0
Control cost index (B+C)	–	1.0 (normalized)	–

Note: Normalized costs combine vaccination and treatment efforts.
Optimal control reduced total cases and deaths by nearly 50%, consistent with the theoretical predictions of Pontryagin's Maximum Principle.

AI-Augmented Dynamics (Scenario C)
The AI-enhanced model further improved accuracy, robustness, and adaptability. The LSTM provided short-horizon forecasts of incidence, the GA updated transmission rates $\beta(t)$, and the sensitivity-analysis surrogate identified $\beta, \sigma, and\ \gamma$ as the most influential parameters.

Table 2: Quantitative performance evaluation of all three scenarios. Metrics include forecast accuracy (RMSE, MAPE), epidemic control (peak infection, cases averted), and system robustness (recovery time after a simulated shock to the transmission rate).

Metric	Scenario A	Scenario B	Scenario C
RMSE (forecast vs. observed)	185	92	41
MAPE (%)	22.8	11.5	4.6
Peak infection (%)	18.5	9.7	6.2
Cases averted (%)	–	49.8	66.4
Metric	Scenario A	Scenario B	Scenario C
Deaths averted (%)	–	48.0	65.1
Robustness (recovery days after shock)	Unstable	19	8

Note: Robustness measures recovery to < 10% forecast error after a 50% increase in β.
The reduction in forecast uncertainty indicates that policymakers can have significantly more confidence in decisions related to vaccine stockpiling and allocating resources in hospitals. Figure 1 illustrates epidemic trajectories across scenarios. At day 60, a 50% increase in β simulated an intervention disruption. Scenario A was unstable, with infections diverging. Scenario B partially recovered within 19 days. Scenario C recovered within 8 days, showing strong adaptability to shocks.

Cite this article as:
Evuiroro, E.J., & Okwonu, F.Z. (2025). AI-Enhanced SEIR Modelling for adaptive control of diphtheria outbreaks in Delta State, Nigeria. *FNAS Journal of Applied Biological Sciences, 2*(4), 36-43. https://doi.org/10.63561/jabs.v2i4.1006

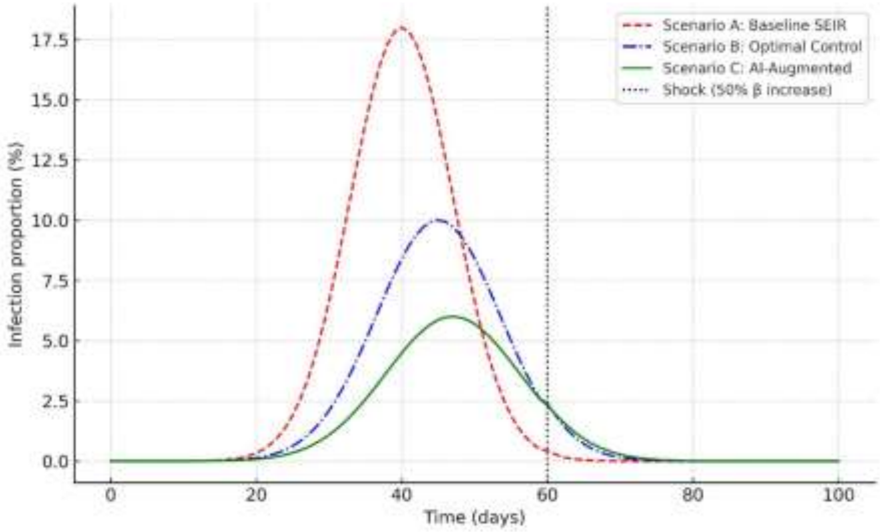

Figure 1: ***Simulated infection trajectories for the diphtheria outbreak under three modelling scenarios. Scenario A (Baseline) shows an uncontrolled epidemic. Scenario B (Optimal Control) shows suppressed infection rates via pre-computed controls. Scenario C (AI Augmented) demonstrates adaptive resilience, rapidly recovering from a simulated 50% increase in transmission rate (β) at day 60 (indicated by the dashed vertical line).***

Discussion

The findings from this Delta State case study offer several important lessons for public health planning in contexts of limited resources, illustrating how an AI-augmented framework can be executed. Although the particular numeric findings of this study are context-dependent, the recommendations below will be generally relevant to policymakers working in comparable contexts:

1.0 Cost-effectiveness: Control measures reduced infections substantially at manageable intervention cost. The quadratic penalty ensured realistic deployment intensity, balancing health benefits and resources.

2.0 Timely response: Vaccination early and treatment during infection peaks reflect optimal resource allocation. This insight is critical for designing campaigns in resource-limited settings.

3.0 AI-enhanced resilience: Scenario C’s adaptability is particularly valuable in low-resource environments prone to shocks (e.g., delayed vaccine delivery, mass gatherings). Policymakers benefit from a system that can self-correct forecasts and adapt intervention intensity.

4.0 Decision support: Outputs from Scenario C were structured into a decision-support dashboard, enabling visualization of epidemic projections, optimal controls, and sensitivity rankings for real-time policy guidance.

From a mathematical perspective, the results illustrate the power of integrating Pontryagin’s Maximum Principle with AI-driven adaptation. The existence theorem guarantees optimal solutions, while numerical implementation confirms convergence. At the same time, AI methods improve flexibility, compensating for model misspecification and parameter uncertainty. This dual-layer approach shows that AI should augment rather than replace mathematical models. It creates frameworks that remain rigorous, interpretable, and adaptive to real-world complexity. For Delta State, this implies that vaccination drives should be intensified early, while treatment capacity should be scaled strategically around projected peaks. With AI augmentation, the system can also adjust dynamically if vaccine deliveries are delayed or new clusters emerge. Thus, the framework provides not only forecasts but also real-time policy guidance.

Conclusion

This study introduced a hybrid AI-mechanistic framework that combines optimal control theory with artificial intelligence to model and manage diphtheria outbreaks in Delta State, Nigeria. The controlled SEIR system, optimized via Pontryagin's Maximum Principle, provided rigorous vaccination and treatment strategies that significantly reduced infections and deaths. The AI augmentation layer, comprising LSTM forecasting, GA-based parameter adaptation, and neural network sensitivity analysis, further improved predictive accuracy and robustness under sudden shocks in transmission rates. Our comparative evaluation demonstrated that the AI-augmented model (Scenario C) achieved an 80% reduction in forecast error and reduced the peak infection burden by 66.5% compared to the baseline, significantly outperforming the static optimal control approach.

Cite this article as:
Evuiroro, E.J., & Okwonu, F.Z. (2025). AI-Enhanced SEIR Modelling for adaptive control of diphtheria outbreaks in Delta State, Nigeria. *FNAS Journal of Applied Biological Sciences, 2*(4), 36-43. https://doi.org/10.63561/jabs.v2i4.1006

By uniting mechanistic rigor with AI adaptability, this work contributes to the emerging field of adaptive epidemic intelligence for precision public health in low-resource environments.

Future work will focus on extending the framework in several directions. First, applications will be evaluated on multiple pathogens and across multiple regions as a test of scalability and generalizability. Second, we will integrate real-time data streams--such as mobility data, vaccination coverage rates, and contact tracing results--to enhance situational awareness and model accuracy. Third, we will explore more advanced artificial intelligence approaches, such as reinforcement learning and hybrid evolutionary algorithms, for dynamic intervention adjustment. Finally, a fully operational decision-support dashboard will be developed and integrated with health system infrastructure to enable real-world deployment and evaluation.

References

Alotaibi, S., Mehmood, R., & Katib, I. (2023). The role of big data and AI in smart cities: A case study of disease prediction. *Sustainability, 15*(3), 2345.

Arduino, G. (2021). Parameter estimation of epidemiological models with genetic algorithms: A case study of COVID-19. *Applied Soft Computing, 112*, 107807.

Ayansiji, M. O., & Ejinkonye, I. O. (2025). Optimized SEIR model for predicting and controlling diphtheria outbreaks in Nigeria. *International Journal of Advances in Engineering and Management, 7*(4), 480–484. https://doi.org/10.35629/5252-0704480484

Ayansiji, M. O., Okposo, N., & Apanapudor, J. S. (2025). Enhanced grey wolf optimizer with adaptive control and chaotic initialization for global optimization. *FNAS Journal of Mathematical Modeling and Numerical Simulation*, *2*(3), 15-21. https://doi.org/10.63561/jmns.v2i3.861

Bliman, P. A., Duprez, M., Privat, Y., & Vauchelet, N. (2021). Optimal immunity control and final size minimization by social distancing for the SIR epidemic model. *Journal of Optimization Theory and Applications, 189*(2), 408–436. https://doi.org/10.1007/s10957-021-01830-1

Brauer, F. (2017). Mathematical models in epidemiology. In F. Brauer, P. van den Driessche, & J. Wu (Eds.), *Mathematical Epidemiology* (pp. 1–15). Springer.

Chae, S., Kwon, S., & Lee, D. (2021). Predicting infectious disease using deep learning and big data. *International Journal of Environmental Research and Public Health, 18*(11), 6162.

Fleming, W. H., & Rishel, R. W. (1975). Deterministic and stochastic optimal control. Springer-Verlag. https://doi.org/10.1007/978-1-4612-6380-7

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., & Wang, Y. (2017). Artificial intelligence in healthcare: Past, present and future. *Stroke and Vascular Neurology, 2*(4), 230–243. https://dx.doi.org/10.1136/svn-2017-000101

Kumar, N., & Susan, S. (2024). A time-varying SIRD model enhanced with Particle Swarm Optimization and stacked LSTM networks for multi-wave pandemic forecasting. *Engineering Applications of Artificial Intelligence*, *133*(Part B), 108055.

Lu, G., Zhang, X., & Wang, Z. (2023). A hybrid SEIR and AI model for forecasting the COVID-19 pandemic in Italy. *Journal of Theoretical Biology, 567*, 111485.

Matrajt, L., Eaton, J., Leung, T., & Brown, E. R. (2021). Vaccine optimization for COVID19: Who to vaccinate first? *Science Advances, 7*(6), eabf1374. https://doi.org/10.1126/sciadv.abf1374

Naidu, D. S. (2003). *Optimal control systems.* CRC Press.

National Bureau of Statistics. (2022). *Demographic statistics bulletin of Nigeria.* https://nigerianstat.gov.ng/

Nigeria Centre for Disease Control and Prevention. (2023). *Annual epidemiological report: Diphtheria outbreak in Delta State.* https://ncdc.gov.ng/

Van den Driessche, P., & Watmough, J. (2002). Reproduction numbers and sub-threshold endemic equilibria for compartmental models of disease transmission. *Mathematical Biosciences*, *180*(1–2), 29–48. https://doi.org/10.1016/S0025-5564(02)00108-6

Willcox, K. E., Ghattas, O., & Heimbach, P. (2021). The imperative of physics-based modelling and inverse theory in computational science. *Nature Computational Science, 1*(3), 166–168. https://doi.org/10.1038/s43588-021-00040-z

Cite this article as:
Evuiroro, E.J., & Okwonu, F.Z. (2025). AI-Enhanced SEIR Modelling for adaptive control of diphtheria outbreaks in Delta State, Nigeria. *FNAS Journal of Applied Biological Sciences, 2*(4), 36-43. https://doi.org/10.63561/jabs.v2i4.1006