

## Generative AI Advisor Framework of MPox Elimination Strategies

Eustache MUTEBA\*

Correspondent of International Medical Informatics Association (IMIA) in DR Congo

**\*Corresponding author:**

Eustache MUTEBA, Correspondent of International Medical Informatics Association (IMIA) in DR Congo.

**ABSTRACT**

In this paper, we designed a Generative AI Advisory Framework (GAIAF) and operationalized our ongoing study called an Artificial Neural Network of Mpx (ANN-MPX). The Generative AI Advisory Framework integrates prompt-based large language models with evolutionary algorithms, creating a closed-loop system that links strategic generation, simulation, and optimization. This framework represents a step toward hybrid AI-driven decision-support tools capable of improving real-time public health intelligence and strategic preparedness. Through a simulated case study, we demonstrate how the system supports dynamic epidemic control planning and intervention for Mpx elimination efforts.

**Keywords:** Generative AI, Artificial Neural Network, Advisory System, Decision Support, MPox Elimination.

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### Introduction

The adoption of artificial intelligence (AI) in public health decision-making has accelerated in recent years, particularly with the rise of neural network-based generative AI systems capable of synthesizing complex information, modeling uncertain outcomes, and supporting strategic planning. Built on deep learning architectures such as transformers and convolutional neural networks, these systems hold significant promise for augmenting public health intelligence enabling innovations in outbreak detection, epidemic forecasting, personalized health messaging, and policy simulation [1-3].

In line with this trajectory, we recently developed the Artificial Neural Network Model of MPox (MPX) Elimination Strategies, a decision-support that combines a classic SIR framework with force of infection and force of elimination sub-models [4]. This ANN-based model provides the capability to forecast disease trajectories and assess the potential impact of candidate elimination strategies.

Building upon this foundation, the present paper introduces a Generative AI Advisory Framework (GAIAF) and operationalized the ANN-MPX model by acting as a “what-if” strategy generator, evaluator, and guide. This is critical for enabling responsive, data-driven decision-making in complex public health contexts, where new strategies must often be generated on the fly and evaluated under uncertainty [5]. Through a simulated case study, we demonstrate how the system supports dynamic epidemic control planning and intervention for Mpx elimination efforts.

### Methods

#### ANN-MPX System

The proposed ANN-MPX system, as stated in, is a hybrid neural-epidemiological modeling framework designed to support real-time MPox (Monkeypox) elimination planning [4]. At its core, it integrates the classical SIR (Susceptible-Infectious-Removed) model with artificial neural network (ANN) elements to enable predictive modeling of disease dynamics. The system uses

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derived epidemiological indicators such as the Force of Infection  $\rho$  and Force of Elimination  $f\varepsilon$ , which respectively quantify transmission intensity and guide elimination strategies [6].

The ANN-MPX architecture, serving as non-linear approximator and decision support engine, is a cascade neural network, comprising the following:

- **Input Layer (Data Sources):** Epidemiological Parameters ( $S_d, I_d, R_d, R_o, n$ ).
- **Neurons:** represent equations from the three epidemiological models.
- **Preprocessing Layer:** normalization of variables, nonlinear transformations using activation functions.
- **Database and Knowledge Base:** stores epidemiological data, demographic data, geospatial data, clinical data, policy data, historical patterns, optimal intervention strategies and contains prior epidemiological parameters and policies, new outbreak data.
- **Output Layer:** predicted states or metrics ( $S_{d+t}, I_{d+t}, R_{d+t}, r, t, \rho_{d+t}, \varepsilon_{d+t}$ ) and decision support output (strategic recommendation, operational guidance, etc.).
- **Feedback Loop and Learning Objective:** feeds back into model refinement or rule-based overrides, human-in-the-loop and minimize prediction error and maximize convergence to low  $f\varepsilon$  values (i.e., toward elimination).

### Generative AI Advisory Framework

To make the ANN-MPX system operational, we design the component Generative AI Advisory Framework (GAIAF) that can generate, evaluate, and optimize public health intervention strategies in real time. GAIAF integrates prompt-based large language models (LLMs) with evolutionary algorithms (EAs), creating a closed-loop system that links strategic generation, simulation, and optimization. These methods allow an interactive simulation and optimization loop designed for responsive strategy generation under uncertainty [7].

#### (a) Strategy Representation

Intervention strategies are encoded into structured vectors:

$$v_i = [\tau_i, \theta_i, \iota_i, \gamma_i, k_i] \quad (1)$$

where  $\tau_i$  denotes intervention type (e.g., vaccination, testing),  $\theta_i$  captures timing parameters (start and end dates),  $\iota_i$  reflects intensity or coverage,  $\gamma_i$  defines the target group (e.g., specific demographics or regions), and  $k_i$  includes constraints (e.g., supply limits, availability of medical personnel).

#### (b) Prompt-Based Transformer Generation

A fine-tuned transformer model generates candidate strategies from scenario-specific prompts. These are context-aware and align with policy norms. Let  $D$  represent the epidemiological context, and  $P$  be a set of structured interventions:

$$v_i^{(0)} = \text{Transformer}(P_i(D)) \quad (2)$$

Strategies generated in this way are semantically coherent and tailored to the outbreak context, reflecting prior knowledge and policy norms embedded in the LLM. This stage supports interpretability and narrative alignment with policymaker needs [8].

#### (c) Feasibility Filtering

Generated strategies are subsequently evaluated against a feasibility filter,  $F(v_i) \in \{0,1\}$ , which enforces hard constraints. These constraints are derived from: public health guidelines, operational logistics, and ethical constraints. Only strategies with  $F(v_i) = 1$  are forwarded for simulation.

#### (d) Evaluation via ANN-MPX Core

Feasible strategies are evaluated by simulating their impact on disease dynamics through the ANN-MPX core. The output includes predicted state variables and updated elimination force  $\varepsilon'(d)$ .

A composite fitness function  $f(v_i)$  is defined as:

$$f(v_i) = \alpha \cdot P_{\text{elim}}(v_i) - \beta \cdot C(v_i) \quad (3)$$

where  $P_{\text{elim}}$  represents the estimated probability of reaching elimination within a specified timeframe, and  $C(v_i)$  represents estimated cost or resource burden. The weights  $\alpha, \beta \in \mathbb{R}^+$  are user-defined and reflect strategic trade-offs (e.g., cost-effectiveness vs. speed of elimination).

#### (e) Optimization with Evolutionary Algorithms

An initial set of strategies,  $V^{(0)} = \{v_1, \dots, v_n\}$ , is generated using transformer-based candidates. An evolutionary algorithm (EA) then performs iterative optimization over generations  $t \in \{1, \dots, T\}$ . This process continues until a convergence threshold is met, typically defined as stabilization of  $f(v_i)$  or attainment of  $\varepsilon(d) < \tau$ , where  $\tau$  is a policy-defined elimination target.

#### (f) Strategy Output and Feedback Loop

Final optimized strategies  $V^*$  are ranked and categorized as follows: strategic recommendations, operational guidance, and policy alerts. A transformer-based advice module produces human-readable outputs, while feedback from experts or field data continuously updates and improves the model.

#### (g) Advice Generation Module

The table 1 is showed rule-based logic derived from WHO Mpox guidelines translates qualitative recommendations into actionable triggers, enhancing decision relevance and context sensitivity.

**Table 1: Sample of Rule Set and Strategic Advice**

Rule	Condition	Advice
1	$f\varepsilon > 40 \rightarrow \text{Phase} = \text{"Active"}$ & Mobility high and $\rho > 0.3$	Implement mobility restrictions and expand surveillance at transit hubs.
2	$f\varepsilon > 40 \rightarrow \text{Phase} = \text{"Active"}$ & Urban zone = True	Prioritize vaccine-first strategy due to high population density.
3	$f\varepsilon > 40 \rightarrow \text{Phase} = \text{"Active"}$ & Neither mobility high nor urban zone	Maintain aggressive suppression, testing, and vaccination.
4	$20 < f\varepsilon \leq 40 \rightarrow \text{Phase} = \text{"Declining"}$	Maintain suppression measures; enhance contact tracing and isolation.

5	$10 < f_{\epsilon} \leq 20 \rightarrow$ Phase = "Declining"	Maintain current suppression; prepare surge capacity if needed.
6	$f_{\epsilon} \leq 10 \rightarrow$ Phase = "Rising" & Public resistance = True and Lockdown = True	Shift to voluntary measures; engage communities.
7	$f_{\epsilon} \leq 10 \rightarrow$ Phase = "Rising" & Not (Public resistance and Lockdown)	No critical issues. Continue monitoring.

## Results

### a) Case Study Problem

The case study focuses on a mid-sized urban population of 10,000 individuals experiencing a simulated MPox outbreak over a 30-day period. The objective of the simulated case study is to evaluate the performance of the ANN-MPX model, analyze how different intervention strategies affect infection dynamics given an infectious period of days, and generate data-driven strategic recommendations for MPox elimination. A synthetic dataset representing daily infection counts was generated to support model evaluation: [5, 15, 35, 60, 100, 150, 300, 500, 700, 1000, 1100, 1050, 980, 920, 850, 800, 750, 700, 650, 600, 580, 560, 540, 520, 500, 480, 460, 300, 120, 30]. The implementation of the system has been developed in Python.

### b) Output

#### Simulation Outcomes Visualization

Population: 10000

Days: 30

Peak infections: 1100 on day 10

Doubling time (early phase): 1.02 days

Susceptible = 9970;

Infectious: 30;

Removed: 0

$r$  (recovery rate) = 0.0625,  $t$  (transmission rate) = 0.1437

Force of Infection ( $\rho$ ) = 0.0074

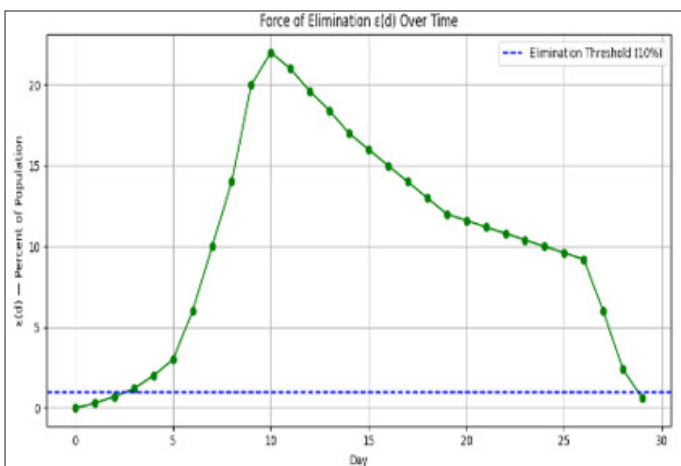
Force of elimination ( $f_{\epsilon}$ ) = 10.95%

ANN confidence = 4.77%

Strategic Assessment:

Phase: Declining

Advice: - Maintain current suppression; prepare surge capacity if needed.



**Figure 1:** Trend of force of elimination

## Discussion and Conclusion

The implementation of the ANN-MPX system demonstrates the operational potential of the Generative AI Advisory Framework (GAI AF) for dynamic strategy evaluation and decision support in MPox elimination. Conceptually, GAI AF operates as a closed-loop architecture that links intervention generation, epidemiological forecasting, and adaptive policy guidance, allowing strategies to be created, tested, and refined dynamically in response to shifting outbreak conditions.

The simulation case study validated GAI AF's capacity to produce context-specific and actionable recommendations. Quantitatively, the system detected a declining epidemic phase, characterized by a low value of Force of Elimination ( $f_{\epsilon} = 10.95\%$ ), indicating progress toward suppression. This metric, unique to the ANN-MPX framework, serves as a strategic indicator that links epidemiological states to actionable intervention intensity. While traditional indicators describe current outbreak levels,  $f_{\epsilon}$  quantifies how close the system is to disease-free equilibrium, thus providing a bridge between epidemic dynamics and control strategy prioritization.

Within this context, the generative components performed complementary roles. The language-based component (Prompt-LLM) responded adaptively to contextual inputs, allowing human expertise to dynamically adjust algorithmic recommendations.

Conversely, the genetic algorithm optimizer prioritized a more conservative strategy to maximize epidemic elimination robustness. This divergence illustrates the hybrid framework's strength, its ability to incorporate both contextual expert reasoning and quantitative optimization into a unified advisory process.

Despite these promising results, several challenges remain. The framework's predictive reliability is contingent on the availability and quality of timely epidemiological data, which can be limited in low-resource settings. Moreover, while generative AI can rapidly propose strategies, continuous validation and human oversight are essential to ensure real-world effectiveness. Ethical considerations surrounding AI-driven interventions, especially those that may restrict mobility or privacy, necessitate transparent governance and human-in-the-loop mechanisms.

In conclusion, the GAI AF-ANN-MPX represents a novel hybrid intelligence system that unites mechanistic modeling, adaptive reasoning, and optimization for dynamic epidemic strategy design. Future work will focus on real-world validation, behavioral modeling, and cross-disease generalization to strengthen its applicability in global health preparedness and outbreak response.

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