

Quantifying Reinfection-Driven COVID-19 Transmission with Physics-Informed Neural Networks

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INTRODUCTION & AIM

The emergence of multiple SARS-CoV-2 variants highlighted the critical role of immune escape, reinfection, and nonstationary transmission dynamics in epidemic evolution. In particular, the co-circulation of the Omicron and Delta variants introduced complex transmission interactions that are difficult to capture using classical epidemic models with constant epidemiological parameters. These limitations reduce the ability of traditional models to characterize evolving variant-specific transmission behavior and epidemic transitions.

To address this challenge, we develop a biologically constrained two-strain COVID-19 framework coupled with physics-informed neural networks (PINNs) to infer hidden time-dependent epidemiological parameters directly from the State of Tennessee COVID-19 surveillance data.

Research Objectives

- Develop a **two-strain COVID-19 framework** for Omicron-Delta dynamics.
- Infer **time-varying epidemiological parameters** through PINNs.
- Perform **phase-wise and scenario-based parameter estimation**.
- Quantify immune escape and asymmetric reinfection dynamics.
- Compute **temporal reproduction numbers** and epidemic forecasts.

METHOD

Data Preprocessing Framework

- Variant decomposition

$$\bar{C}_1(t) = s(t)\bar{C}(t), \quad \bar{C}_2(t) = (1 - s(t))\bar{C}(t)$$

- Recovery and death allocation

$$\bar{R}_k(t) = \frac{\bar{I}_k(t-1)}{\bar{I}_1(t-1) + \bar{I}_2(t-1)} \bar{R}(t), \quad \bar{D}_k(t) = \frac{\bar{I}_k(t-1)}{\bar{I}_1(t-1) + \bar{I}_2(t-1)} \bar{D}(t)$$

- Active infection update

$$\bar{I}_k(t) = \max(0, \bar{I}_k(t-1) + \bar{C}_k(t) - \bar{R}_k(t) - \bar{D}_k(t))$$

- Susceptible reconstruction

$$\bar{S}(t) = N - \bar{I}_1(t) - \bar{I}_2(t) - \bar{R}_1(t) - \bar{R}_2(t), \quad N = 7.05 \times 10^6$$

The proposed **two-strain framework** incorporates strain-specific transmission and asymmetric reinfection dynamics:

$$\begin{aligned} \dot{S} &= \Lambda - \beta_1(t)SI_1 - \beta_2(t)SI_2 - \mu(t)S, \\ \dot{I}_1 &= \beta_1(t)SI_1 + \tilde{\beta}_1(t)R_2I_1 - (\gamma_1(t) + \omega_1(t) + \mu(t))I_1, \\ \dot{I}_2 &= \beta_2(t)SI_2 + \tilde{\beta}_2(t)R_1I_2 - (\gamma_2(t) + \omega_2(t) + \mu(t))I_2, \\ \dot{R}_1 &= \gamma_1(t)I_1 - \tilde{\beta}_2(t)R_1I_2 - \mu(t)R_1, \\ \dot{R}_2 &= \gamma_2(t)I_2 - \tilde{\beta}_1(t)R_2I_1 - \mu(t)R_2. \end{aligned}$$

Here, $\beta_i(t)$ are primary transmission rates, $\tilde{\beta}_i(t)$ are reinfection rates, $\gamma_i(t)$ are recovery rates, and $\omega_i(t)$ are mortality rates.

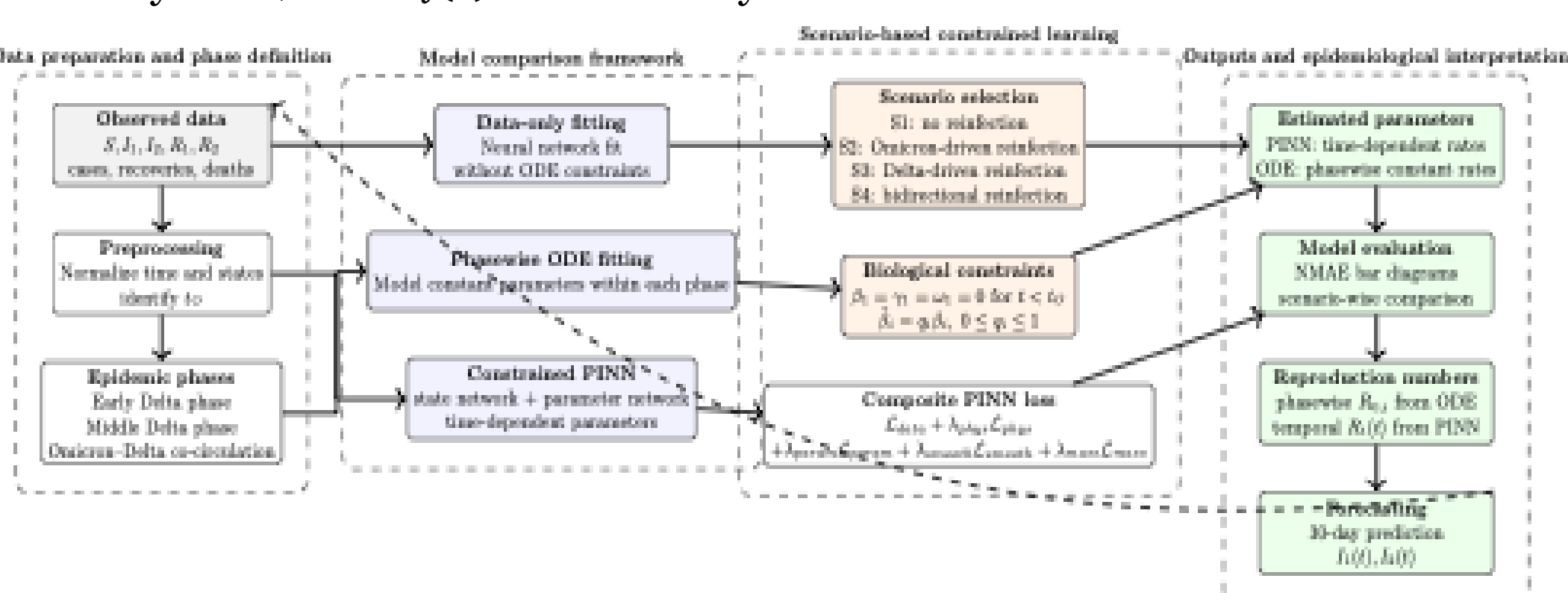


Figure 1: Scenario-based PINN framework for multi-strain COVID-19 parameter estimation and epidemic forecasting.

RESULTS & DISCUSSION

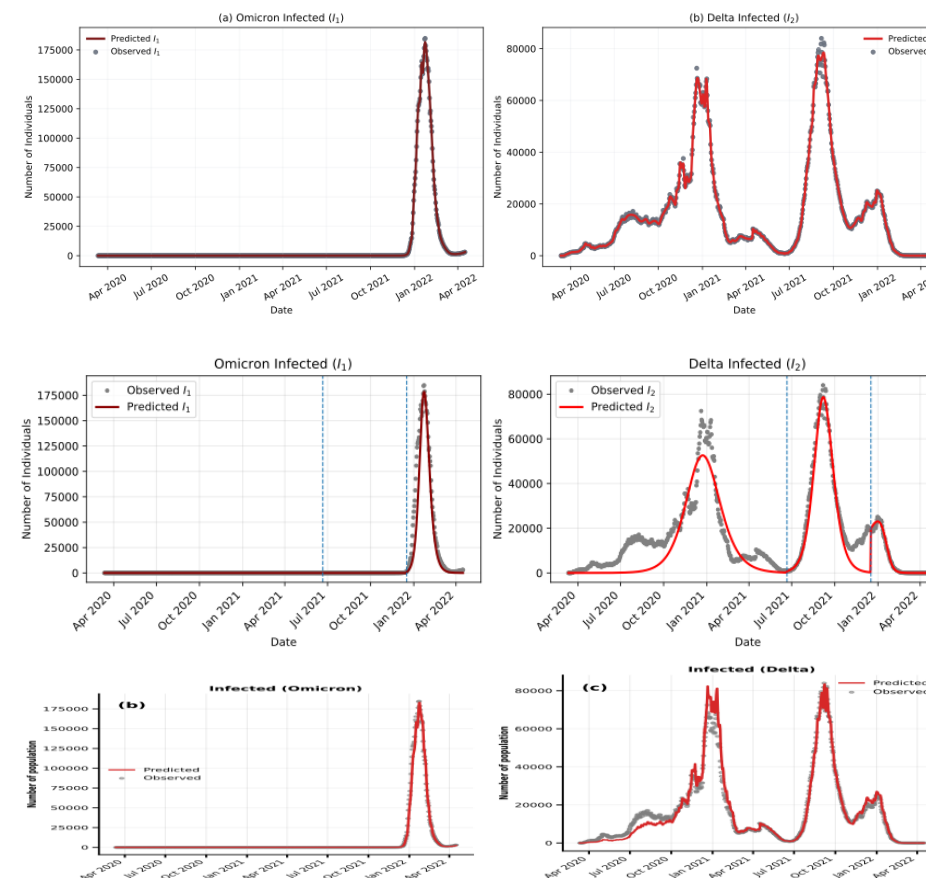


Figure 2: Comparison of neural network, phase-wise ODE, and constrained PINN fitting strategies for the two-strain COVID-19 framework. The constrained PINN approach provided the most accurate reconstruction of the epidemiological trajectories by integrating observational data with biological and dynamical constraints, while phase-wise fitting improved stability relative to data-only neural network estimation.

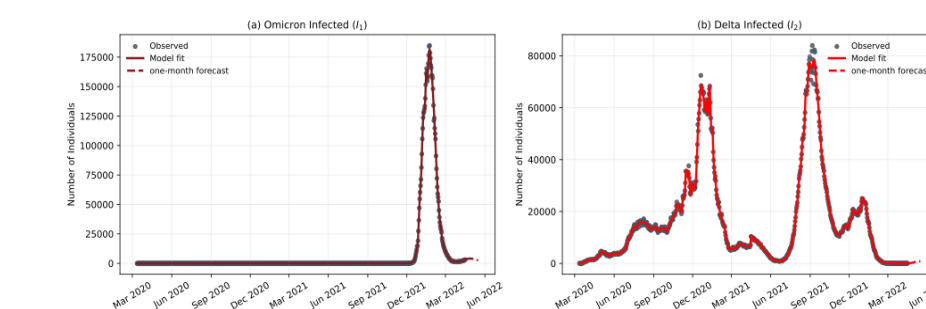


Figure 5: Short-term forecasting results obtained using the constrained PINN framework. The model accurately reproduced variant-specific epidemic transitions and captured the temporal evolution of infection trajectories during the Omicron-Delta co-circulation phase.

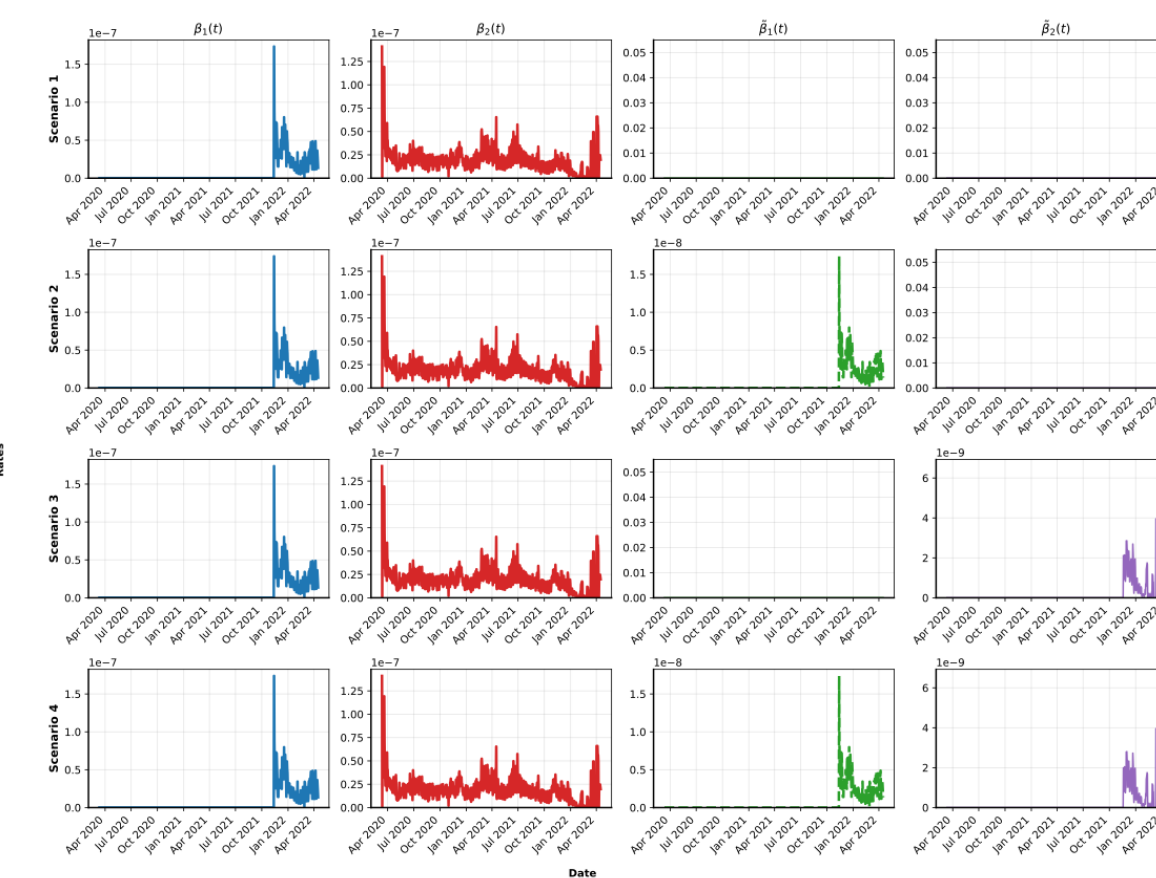


Figure 3: Time-dependent transmission and reinfection rates estimated using the constrained PINN framework under four distinct reinfection scenarios. The Omicron transmission rate exhibited substantially stronger temporal variability during the co-circulation phase, while reinfection rates remained consistently lower than primary transmission rates across all scenarios. These results suggest that immune escape primarily contributed to sustained epidemic persistence and cross-variant transmission rather than acting as the dominant driver of initial epidemic growth.

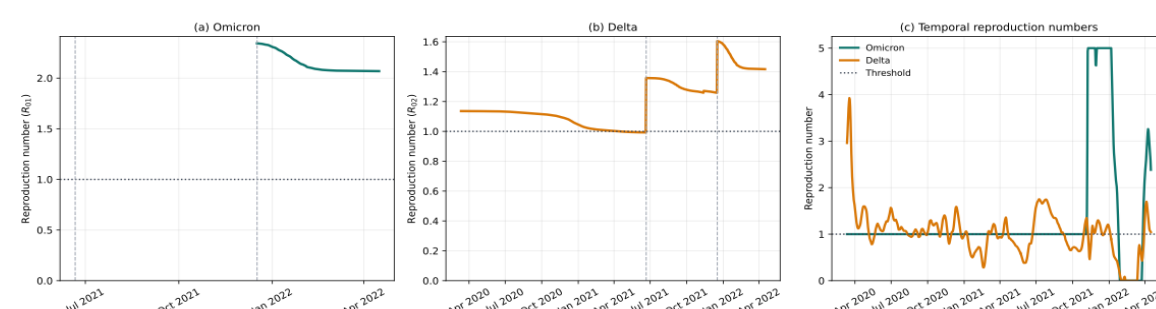


Figure 4: Comparison between phase-wise basic reproduction numbers and temporally evolving reproduction numbers estimated using the PINN framework. The temporal reproduction numbers captures rapid transmission changes during the Omicron emergence period, demonstrating the advantage of continuous time-dependent parameterization over phase-wise constant epidemic assumptions.

CONCLUSION

The proposed constrained PINN framework accurately reconstructed Omicron-Delta epidemic dynamics and enabled continuous estimation of time-dependent transmission and reinfection parameters, demonstrating that temporally evolving epidemiological processes are essential for characterizing multi-strain COVID-19 transmission dynamics.

FUTURE WORK / REFERENCES

Islam, M.S., and Wang, J. Quantifying Reinfection-Driven COVID-19 Transmission with Physics-Informed Neural Networks; manuscript under review.