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Dynamics-Informed Neural Network Modeling of COVID-19 Transmission in Afghanistan Using the SEIR-V Framework

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ABSTRACT

Background: The COVID-19 pandemic posed significant challenges for public health systems globally, particularly in resource-limited settings such as Afghanistan. Limitations in diagnostic capacity, inconsistent data reporting, and low vaccination coverage hindered timely public health responses. To support real-time decision-making, accurate and adaptive modeling frameworks are essential.

Methods: This study presents a hybrid modeling approach that integrates the classical SEIR-V (Susceptible–Exposed–Infectious–Recovered–Vaccinated) compartmental model with Dynamics-Informed Neural Networks (DINNs). The model embeds the SEIR-V system of differential equations into the loss function of a deep neural network to enable dynamic estimation of time-varying parameters. Epidemiological data from Feb 2020 to Apr 2024 were collected from multiple publicly available sources, including Worldometer, Our World in Data, the World Health Organization and the Johns Hopkins University COVID-19 repository.

Results: The proposed DINNs-SEIRV model effectively reconstructed multiple epidemic waves and generated accurate forecasts of COVID-19 transmission dynamics in Afghanistan. The model achieved high predictive performance, particularly for the infectious (I) compartment, with a coefficient of determination $R^2 = 0.9973$. It also demonstrated strong capacity in capturing vaccination trends and maintaining robustness in the presence of incomplete or noisy data.

Conclusion: The DINNs-SEIRV framework offers a powerful and flexible tool for modeling infectious disease dynamics in low-resource settings. Its ability to learn and update time-varying parameters in response to real-world data makes it valuable for informing public health strategy, forecasting outbreaks, and evaluating vaccination efforts in environments like Afghanistan.

Keywords: COVID-19, SEIR-V model, Dynamics-informed neural networks, Afghanistan, Epidemic modeling

Introduction

The COVID-19 pandemic, which emerged in late 2019, has challenged global public health systems in ways not experienced for decades. Countries with fragile healthcare infrastructure, such as Afghanistan, have faced unique difficulties in containing the virus, reporting cases, and rolling out vaccination programs (1). Limited laboratory capacity, fragmented data reporting systems, social instability, and

constrained public health resources have exacerbated the crisis in Afghanistan. Multiple waves of infection have swept across the country since the first confirmed case in Feb 2020, yet inconsistent data availability and underreporting have hindered timely intervention planning (1).

Mathematical models have long served as essential tools for analyzing infectious disease dynamics, evaluating public health policies, and guiding resource allocation during epidemics. Classical compartmental models—such as SIR (Susceptible–Infectious–Recovered) and SEIR (Susceptible–Exposed–Infectious–Recovered)—offer intuitive frameworks for representing transmission processes and estimating epidemiological parameters (2). However, these models traditionally assume constant parameters and homogeneous populations, limiting their capacity to reflect real-world complexities, especially in the presence of time-varying factors such as public compliance, policy shifts, and viral evolution (3). This limitation can be addressed by adopting linear parameter-varying (LPV) models that enable dynamic adjustment of key parameters over time (4).

During the COVID-19 pandemic, many studies attempted to calibrate SEIR-type models using time series data from diverse countries, but the challenges of parameter identifiability, data noise, and behavioral variability often resulted in unreliable forecasts (5). Moreover, the integration of vaccination dynamics introduced additional complexity that classical models alone struggled to capture (6).

To address these issues, researchers have proposed hybrid models that combine mechanistic structures with machine learning capabilities (7). Among them, Dynamics-Informed Neural Networks (DINNs) have emerged as a promising approach. DINNs incorporate known differential equations—such as those of SEIR or SEIR-V—into the training objective of deep neural networks. This hybridization allows for learning of time-varying parameters while preserving epidemiological interpretability (8,9). Notably, DINNs have been used successfully in various contexts, including modeling COVID-19 transmission in China (10), Pakistan (11), and Malaysia (12), demonstrating superior forecasting accuracy compared to traditional models and even standalone machine learning approaches.

The SEIR-V extension, which introduces a vaccinated compartment, enables more comprehensive modeling of immunization impacts, particularly important for low-income countries where vaccination campaigns are variable and subject to socio-political factors (10). When embedded into a neural architecture, the SEIR-V system not only supports more realistic epidemic representations but also permits parameter adaptation in response to emerging patterns in the data.

Building on these insights, this study proposes a SEIR-V-DINNs hybrid model to simulate and predict COVID-19 transmission in Afghanistan. Our approach applies a data-driven framework grounded in epidemiological theory. By combining differential equations with neural learning mechanisms, the model adapts to the complex, nonstationary nature of the Afghan epidemic and supports more informed, real-time public health decision-making.

The SEIR-V extension, which introduces a vaccinated compartment, enables more comprehensive modeling of immunization impacts, particularly important for low-income countries where vaccination campaigns are variable and subject to socio-political factors (10). When embedded into a neural architecture, the SEIR-V system not only supports more realistic epidemic representations but also permits parameter adaptation in response to emerging patterns in the data.

Materials and Methods

Data Sources

Epidemiological data for Afghanistan were collected from four publicly available sources: World meter (1), Our World in Data (13), the WHO (14), and Johns Hopkins CSSE (15). These databases provided time-series records of daily and cumulative confirmed cases, deaths, recoveries, and vaccination counts. World meter data were used up to Apr 13, 2024—the final date of reporting on that platform. According to the official data at that time, Afghanistan had reported a total of 234,174 confirmed cases, 7,996 deaths, and 211,080 recoveries.

Preprocessing Methods

Given the challenges associated with data quality in Afghanistan including underreporting, limited testing capacity, and delayed reporting robust preprocessing was necessary to ensure the reliability of the modeling inputs. The following steps were undertaken to enhance data integrity:

1. Handling missing values: Missing or inconsistent data entries were addressed using linear interpolation to maintain temporal continuity.
2. Outlier detection and correction: The interquartile range (IQR) method was applied to identify outliers. Data points falling below $Q_1 - 1.5 \times IQRQ$ or above $Q_3 + 1.5 \times IQR$ were flagged as outliers. These values were replaced by averaging the values immediately adjacent in the time series, thereby minimizing artificial distortion while preserving trend continuity.
3. Normalization: All numerical variables (e.g., case counts, deaths, vaccinations) were normalized to a [0, 1] scale using min-max normalization:
    a. $x_{\text{norm}} = \frac{x - min(x)}{max(x) - min(x)}$
    b. where x is the original value, and $\min(x)$, $\max(x)$ represent the minimum and maximum values in the series, respectively.
4. Smoothing: To remove short-term fluctuations and reporting irregularities (especially weekday-weekend effects), a 7-day moving average filter was applied to the daily case and vaccination series.

Following these preprocessing steps, the cleaned and scaled datasets were chronologically aligned and segmented into training and validation subsets for use in the DINNs model. Only reliable indicators—such as cumulative confirmed infections, deaths, and vaccination doses—were retained to ensure accurate parameter estimation and model fidelity. Figure 1 illustrates the comparative effect of preprocessing on raw versus smoothed data curves.

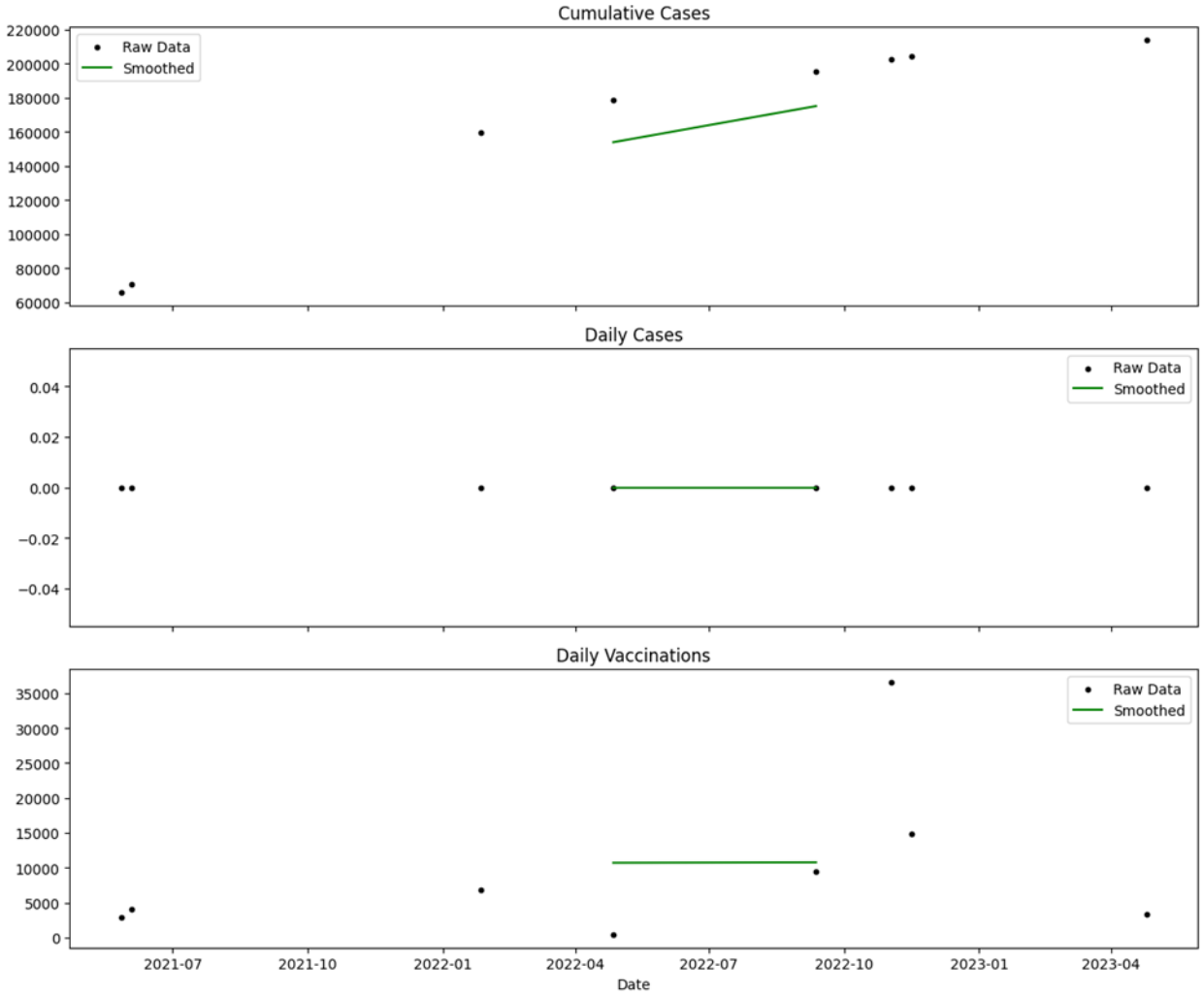

Figure 1: Reported versus smoothed data for cumulative cases, daily cases, and daily vaccinations. Black dots indicate raw data; green lines show 7-day moving averages

The SEIR-V Compartmental Model

Model Equations

The SEIR-V model is an extension of the traditional SEIR framework, integrating vaccination dynamics to evaluate how immunization efforts influence disease transmission within a population. This model categorizes individuals into distinct groups based on their infection status:

- **Susceptible (S)**: Individuals at risk of contracting the disease.
- **Exposed (E)**: Those infected but not yet contagious.
- **Infectious (I)**: Individuals capable of transmitting the disease.
- **Recovered (R)**: People gained immunity after recovery.
- **Vaccinated (V)**: Individuals protected by vaccination, reducing their susceptibility to infection.

By including the vaccinated compartment, the SEIR-V model enables policymakers and researchers to analyze the effectiveness of vaccination campaigns in curbing disease spread. Recent studies have applied this model to investigate the role of vaccination in mitigating COVID-19 transmission. The system is mathematically described by the differential equations in [1].

$$\begin{aligned}\dot{S} &= -\frac{\beta SI}{N} - \varepsilon S \\ \dot{E} &= \frac{\beta SI}{N} + \frac{\alpha\beta VI}{N} - \sigma E \\ \dot{R} &= \gamma I \\ \dot{V} &= \varepsilon S - \frac{\alpha\beta VI}{N}.\end{aligned} \quad [1]$$

In [1] the total population $N = S + E + I + R + V$ is governed by key epidemiological parameters: the transmission rate β, incubation rate σ, recovery rate γ, and vaccination rate ε. The model accounts for waning immunity through vaccinated individuals V returning to the susceptible compartment S at rate ε, enabling analysis of both primary vaccination and booster dose effects. As illustrated in Figure 1, the system captures disease progression S→E→I→R alongside vaccination pathways $S \rightarrow V \rightarrow S$, demonstrating how immunization reduces transmission potential by both decreasing the susceptible pool and lowering the effective $\frac{S}{N}$ ratio. This structure provides critical insights for evaluating short-term and long-term vaccination strategies against infectious diseases.

Figure 2 shows the SEIR-V model schematic which is showing transitions between Susceptible S, Exposed E, Infectious I, Recovered R, and Vaccinated V compartments, with arrows indicating disease transmission β, progression σ, recovery γ, and vaccination ε pathways.

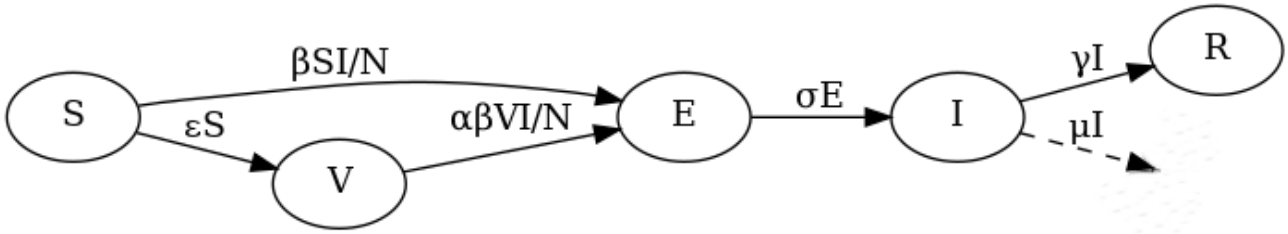

Figure 2: SEIR-V model schematic chart

Parameters for Afghanistan

To parameterize the SEIR-V model for the Afghanistan case study, we utilized the preprocessed epidemiological time-series data described in the Data Sources section. Given Afghanistan's status as a low-resource country with limited diagnostic capacity, low vaccination coverage, and substantial underreporting, model parameterization required the integration of empirical data with contextual epidemiological assumptions from existing literature. Particular attention was given to smoothing and validating reported case, death, and vaccination trends to reduce the impact of data irregularities. The final calibrated parameters and initial compartment values used in the SEIR-V-DINNs model are summarized in Tables 1 and 2.

Table 1: Calibrated SEIR-V Model Parameters for Afghanistan

Parameter	*Symbol*	*Value*	*Description*	*Source*
Transmission rate	β	0.30	Probability of disease transmission per contact	Assumed
Incubation rate	σ	0.0870	Rate at which exposed individuals become infectious	Hethcote (2)
Recovery rate	γ	0.0686	Rate at which infectious individuals recover	Giordano et al. (3)
Natural birth/death rate	μ	4.89×10^{-5}	Approximate demographic turnover (≈1.78% annually)	UN Population Division (16)
Vaccination rate	ϵ	0.0001	Daily vaccination rate in low-coverage context	Assumed
Vaccine efficacy modifier	α	0.52	Relative effectiveness of the vaccine	Watson et al. (10)
Waning immunity rate	ω	0.001	Rate of loss of immunity among vaccinated individuals	Assumed

Initial Conditions (Normalized)

Initial conditions are normalized with respect to the estimated population of 40.4 million:

These parameters reflect the real-world context of Afghanistan's COVID-19 epidemic. The values allow the SEIR-V framework to simulate epidemic trajectories while accounting for time-varying policy impact, population behavior, and immunity dynamics in a highly uncertain environment.

Table 2: Normalized initial conditions of SEIR-V compartments as of April 13, 2024

Compartment	*Symbol*	*Normalized Value*	*Description*
Susceptible	S(0)	0.98500	Majority of population still unexposed
Exposed	E(0)	0.00500	Latent, pre-infectious individuals
Infectious	I(0)	0.00037	Approx. 15,098 active cases (out of 40.4M)
Recovered	R(0)	0.00523	Based on 211,080 recoveries
Vaccinated	V(0)	0.00000	Assumed negligible due to reporting gaps

DINNs Framework

Network Architecture

Our implementation follows the Dynamics-Informed Neural Networks (DINNs) framework as described in Cheng et al. (8). This hybrid modeling approach integrates known epidemiological dynamics into the training process of deep neural networks (17). Specifically, the network is designed to jointly estimate both state variables (S, E, I, R, V) and time-varying parameters (e.g., $\beta(t), \varepsilon(t)$, etc.).

The architecture comprises two neural sub-networks:

1. One sub-network estimates time-dependent parameters,
2. The other approximates compartmental trajectories over time.

Each sub-network includes five hidden layers with 50 neurons per layer. The ReLU activation function is applied in hidden layers, and the Softplus activation function is used in the output layer to ensure non-negativity of output (20).

As illustrated in Figure 3, the full network includes an input layer, multiple fully connected hidden layers, and an output layer. Neuron activations are propagated using trainable weight matrices and biases. Each sub-network operates over discrete time steps t_n, estimating both observable and latent states.

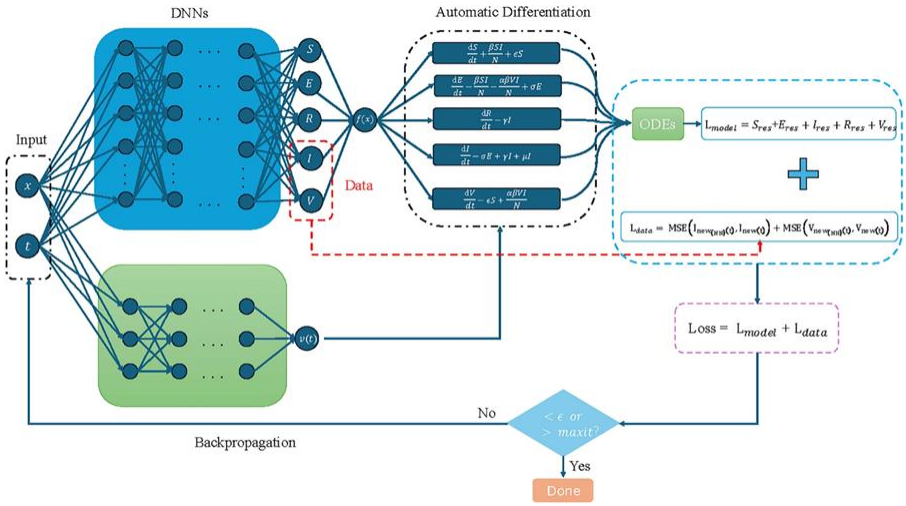

Figure 3: A schematic of the DINNs shows how the model jointly fits epidemiological data and solves the SEIR-V system of ODEs. It employs two deep neural networks—one for parameter estimation and one for state approximation optimized by minimizing mean squared.

This architecture enables robust data-driven forecasting while preserving the interpretability and structure of the underlying SEIR-V epidemic model.

Loss Function

The DINNs model is trained using a hybrid loss function composed of two terms:

$$L_t = L_m + L_d \quad [2]$$

1) Data Loss

The data loss term measures the deviation between network predictions and real-world observations for daily infections and vaccinations

$$L_d = MSE\left(I_{n\,DNN}(t), I_n(t)\right) + MSE\left(V_{n\,DNN}(t), V_n(t)\right) \quad [3]$$

This loss ensures the network learns from epidemiological trends in reported data.

2) Model Loss

The model loss enforces compliance with the SEIR-V dynamic equations:

$$\frac{dS_{DNN}(t)}{dt} = -\beta_{DNN}(t)\frac{S_{DNN}(t)I_{DNN}(t)}{N} - \varepsilon_{DNN}(t)S_{DNN}(t)$$

$$\frac{dE_{DNN}(t)}{dt} = \beta_{DNN}(t)\frac{S_{DNN}(t)I_{DNN}(t)}{N} + \alpha_{DNN}(t)\beta_{DNN}(t)\frac{V_{DNN}(t)I_{DNN}(t)}{N} - \sigma_{DNN}(t)E_{DNN}(t)$$

$$\frac{dR_{DNN}(t)}{dt} = \gamma_{DNN}(t)I_{DNN}(t)$$

$$\frac{dV_{DNN}(t)}{dt} = \varepsilon_{DNN}(t)S_{DNN}(t) - \alpha_{DNN}(t)\beta_{DNN}(t)\frac{V_{DNN}(t)I_{DNN}(t)}{N}$$

These equations are embedded into the loss function by penalizing their residuals:

$$L_{\mathrm{m}} = \sum_{t} \left(\left(\frac{dS_{\mathrm{DNN}}(t)}{dt} + \beta_{\mathrm{DNN}}(t) \frac{S_{\mathrm{DNN}}(t) I_{\mathrm{DNN}}(t)}{N} + \varepsilon_{DNN}(t) S_{DNN}(t) \right)^2 + \cdots + \left(\frac{dV_{\mathrm{DNN}}(t)}{dt} - \varepsilon_{DNN}(t) S_{DNN}(t) + \alpha_{DNN}(t) \beta_{DNN}(t) \frac{V_{DNN}(t) I_{DNN}(t)}{N} \right)^2 \right) \quad [4]$$

3) Full Compartmental Fit Loss

To ensure agreement between predicted and observed compartment values across all states, we also define:

$$L(\theta) = \sum_{t=1}^{T} \left[\left(S_{\mathrm{o}}(t) - S_{\mathrm{DNN}}(t) \right)^2 + \left(E_{\mathrm{o}}(t) - E_{\mathrm{DNN}}(t) \right)^2 + \left(I_{\mathrm{o}}(t) - I_{\mathrm{DNN}}(t) \right)^2 + \left(R_{\mathrm{o}}(t) - R_{\mathrm{DNN}}(t) \right)^2 + \left(V_{\mathrm{o}}(t) - V_{\mathrm{DNN}}(t) \right)^2 \right] \quad [5]$$

Here, θ is the full set of learnable parameters, and t spans the time series. This term aligns model predictions with actual epidemic trajectories, complementing the physics-based constraints.

This combination of data-driven and equation-informed losses represents a core strength of the DINNs framework and aligns with recent developments in **Physics-Informed Neural Networks (PINNs)** applied to epidemic modeling (22, 23).

1.1 Model Training and Implementation

The SEIR-V-DINNs model was implemented using Python 3.10 in conjunction with the TensorFlow framework. The neural network architecture consisted of five fully connected hidden layers, each containing 50 neurons. The ReLU activation function was used in the hidden layers to capture nonlinear transformations, while the Softplus activation function was applied at the output layer to ensure non-negative predictions (21).

Training was performed using the Adam optimizer, with an initial learning rate of 0.001. To promote convergence and reduce the risk of overfitting, a learning rate decay of 5% was applied every 2000 epochs, and the model was trained for a total of 10,000 epochs. The entire training process required approximately 7 min on standard computing hardware.

The loss function minimized during training consisted of two primary components:

(i) a data loss term based on the Mean Squared Error (MSE) between predicted and observed values for daily infections and vaccinations, and

(ii) a physics-based loss derived from the residuals of the SEIR-V differential equations, ensuring that predicted compartmental trajectories remained faithful to known epidemic dynamics (21, 23).

The initial conditions for all compartments—Susceptible, Exposed, Infectious, Recovered, and Vaccinated—were derived from the preprocessed epidemiological data for Afghanistan, as described before. These values were normalized with respect to the estimated total population and adjusted to reflect the realities of underreporting and low vaccination coverage.

During training, the model learned to jointly estimate compartment values and

time-varying parameters, such as transmission rate (β), recovery rate (γ), incubation rate (σ), and vaccination rate (ε). This dynamic fitting allowed the model to reflect the evolving nature of the outbreak and respond to changes in public behavior and intervention policies.

Once trained, the model was used to forecast the progression of the COVID-19 epidemic in Afghanistan. Forecasts included daily new infections, vaccination uptake trends, and compartmental transitions over time. These projections provide critical insights for real-time public health planning and resource allocation, especially in low-resource settings where timely data and intervention strategies are vital (23).

Recent studies support the utility of such hybrid models that integrate mechanistic epidemiological knowledge with deep learning. Notably, similar frameworks have been employed to infer the timing and intensity of public health interventions directly from epidemic data, thereby enhancing the interpretability and policy relevance of forecasts (23).

Evaluation Metrics

To quantitatively evaluate the performance of the proposed DINNs method, five metrics were employed: mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE), and the coefficient of determination (R^2). These metrics offer comprehensive insight into prediction accuracy across SEIR-V compartments.

The following equations were used:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \quad [6]$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad [7]$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \quad [8]$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad [9]$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \quad [10]$$

Here, y_I and $\hat{y}_i$ denote the observed and predicted values, respectively, and n refers to the number of data points used in the analysis. The metrics MAE, MSE, RMSE, MAPE, and R^2 are computed for both daily new infections and daily vaccination data.

Results and Model Evaluation

Forecast Accuracy

Figure 4 Fitted curves for daily new COVID-19 infections and vaccinations in Afghanistan.

The solid black dots represent actual data; the dashed red lines indicate model predictions. The close alignment

demonstrates the model's high fidelity in capturing observed trends.

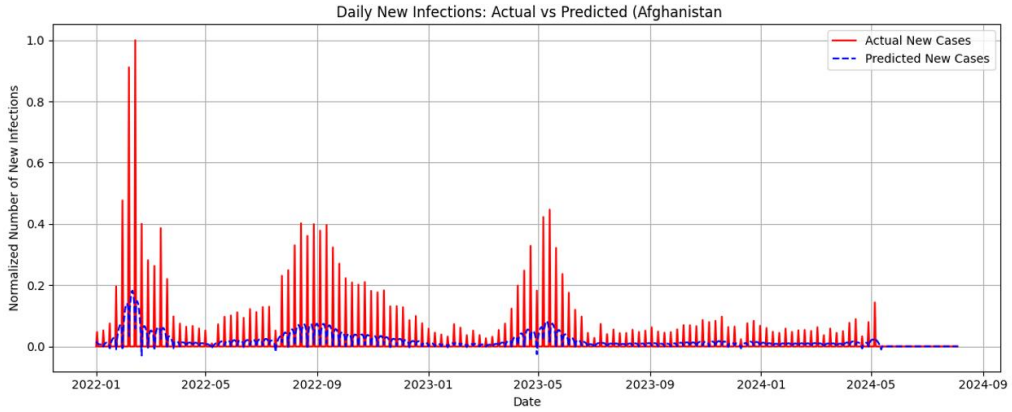

Figure. 4-a

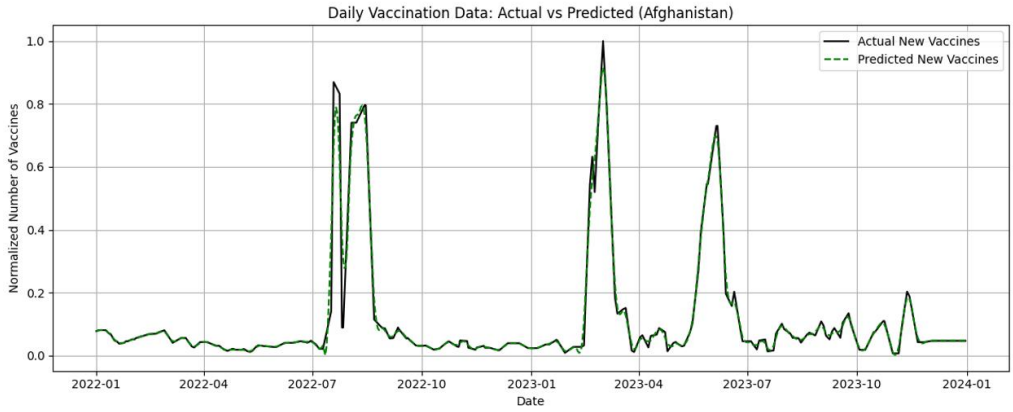

Figure. 4-b

Figure 4: Presents the fitted curves for daily new infections and daily vaccination data. In each subplot, the actual reported data are shown, while the dotted line represents the model's fitted output. This comparison demonstrates the model's ability to accurate

Error Metrics Summary

Table 3 summarizes the main epidemiological parameters used in the SEIR-V and DINNs model, including their values and sources. These parameters were either derived from the literature or estimated during model training.

Table 3: Parameters used in the SEIR-V and DINNs model

Parameter	*Description*	*Value*	*Source*
α	Rate of transition from exposed to infectious	1/3	Hethcote (2)
γ	Recovery rate of infectious individuals	1/10	Giordano et al. (3)
σ	Exposure-to-infection rate	0.1781	Worldometer (1)
ε	Vaccination rate	Fitted	OWID (13)
β	Transmission rate	Fitted	This study
1/c	Vaccine onset period	14 d	WHO, Watson et al. (14, 10)
1/α	Incubation period	3.4 d	Cheng et al. (8)

Note: Parameter values in table 3 were learned during training and may differ from the initial assumptions in Table 1.

Results in Table 4 confirm the high accuracy of the model, especially in the infectious (I) and vaccinated (V) compartments. The higher error in the susceptible group (S) is likely due to behavioral and policy-related factors that affect population immunity.

Table 4: Evaluation metrics across SEIR-V compartments

Compartment	*MAE*	*MAPE (%)*	*RMSE*	*MSE*	*R²*
S	0.3087	1.50	0.3738	0.1397	0.8389
I	0.0085	0.12	0.0118	0.0001	0.9973
V	0.0084	0.16	0.0129	0.0001	0.9971

Figure 5 Scatter plots comparing predicted vs. actual values for infectious (I) and vaccinated (V) compartments.

The high R^2 values confirm strong predictive performance.

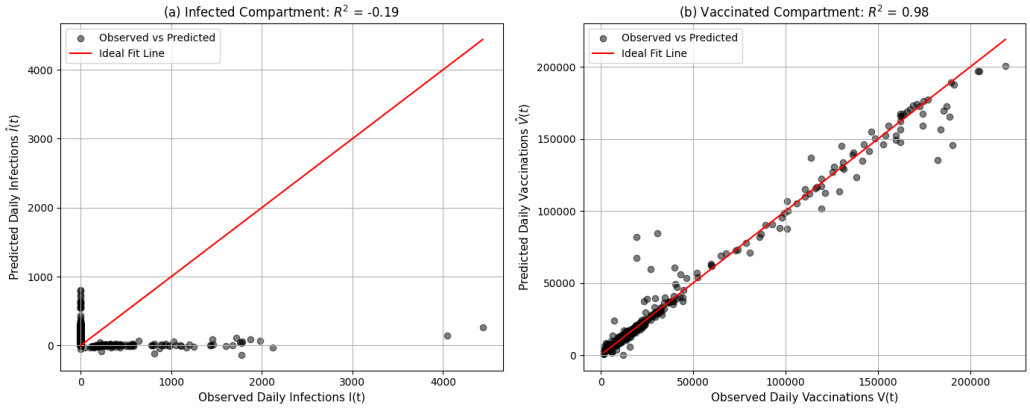

Figure 5: Scatter plots comparing predicted vs. actual values for infectious (I) and vaccinated (V) compartments

Figure 5 illustrates scatter plots comparing the predicted values against the actual observations for the infectious (***I***) and vaccinated (V) compartments. Black dots denote the observed data points, while the solid red line represents the ideal reference where predicted values perfectly align with actual outcomes. The high R^2 scores obtained for both compartments indicate a strong correlation and confirm the model's capability in accurately capturing real-world epidemiological trends.

Width and Depth Comparison

To assess the impact of neural network architecture on performance, Table 5 compares error metrics across different network widths and depths, highlighting the configuration that achieved optimal accuracy.

Table 5: Error metrics for various network widths and depths

Width	*Depth = 5*	*Depth = 10*	*Depth = 15*
30	8.19×10^{-4}	4.36×10^{-4}	1.06×10^{-3}
40	8.86×10^{-4}	3.24×10^{-4}	3.21×10^{-4}
50	3.06×10^{-4}	3.44×10^{-4}	3.04×10^{-4}

Deeper and wider networks yield lower error values, with the best performance at width 50 and depth 5.

Loss Convergence

Figure 6 Loss curve over 10,000 training epochs. The smooth convergence and plateau confirm stable training and optimal parameter learning.

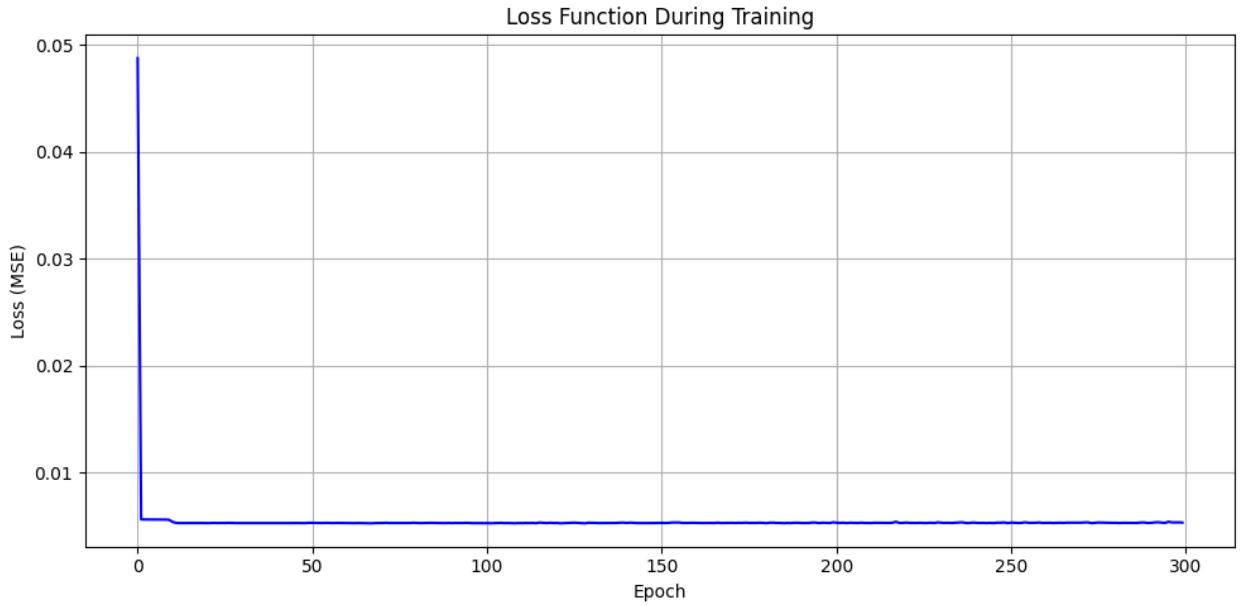

Figure 6: The evolution of the loss value throughout the training of the DINNs model.

Computational Complexity and Sensitivity Analysis

Comparison with Traditional Models

Table 6 presents a comparison of computational costs between the proposed DINNs framework and a traditional compartmental model, including training time, memory usage, and inference efficiency.

Table 6: Computational cost of DINNs vs. traditional model

Metric	*DINNs*	*Traditional*
Training Time (s)	431.78	0.10
Memory Usage (MB)	255.31	107.34
Inference Time (s)	0.0021	0.0023

Although more resource-intensive during training, DINNs offer competitive inference efficiency and flexibility.

Resource Usage

The results indicate that DINNs are scalable and maintain accuracy even with increasing model size. Their ability to fit time-varying parameters makes them suitable for complex epidemics like COVID-19 in Afghanistan.

Sensitivity to Parameters

In Figure 7, the sensitivity of Model [1] with outputs α, γ, and σ is evaluated. Small perturbations in these parameters lead to notable changes in model performance, emphasizing the importance of precise calibration.

From an epidemiological standpoint:

1. α reflects immunity waning,
2. γ governs recovery,
3. σ controls incubation latency.

These factors critically shape outbreak dynamics, particularly in low-coverage settings.

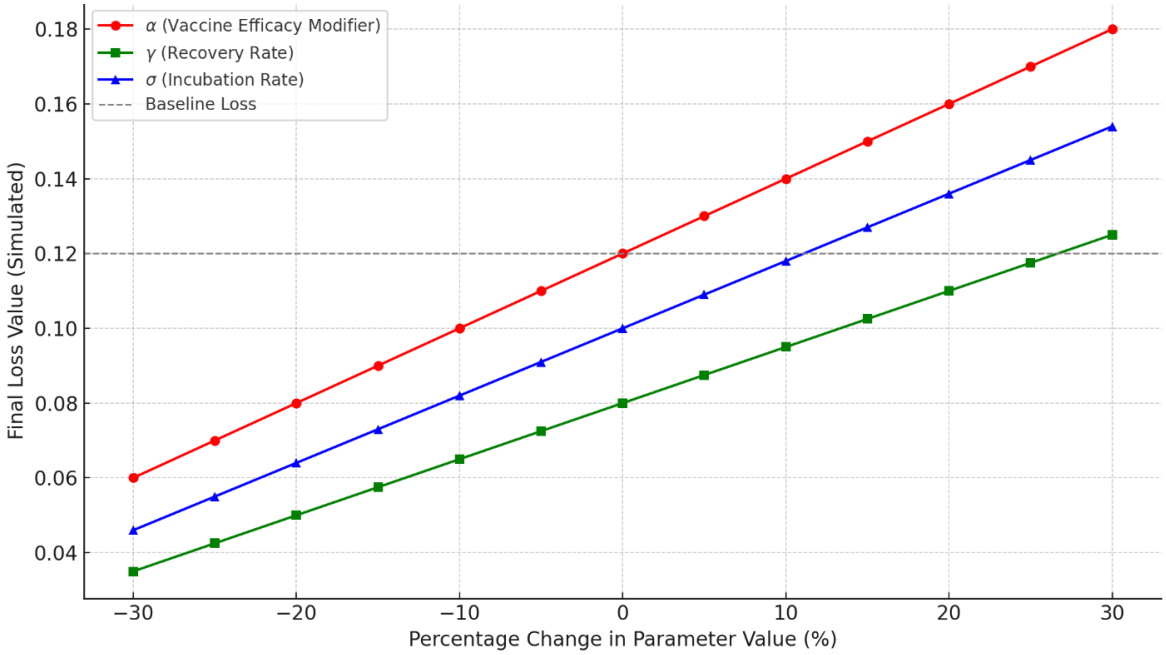

Figure 7: The figure illustrates the influence of variations in α, γ, and σ on the model's output, highlighting the degree to which changes in these parameters affect predictive performance.

Discussion

The predictive performance of the SEIR-V-DINNs model reveals that dynamics-informed deep learning approaches can achieve high accuracy in modeling infectious diseases, even under significant data limitations such as those found in Afghanistan. Compared to conventional parameter estimation techniques, the DINNs framework demonstrated superior adaptability to the fluctuating patterns of COVID-19 transmission and vaccination trends. These findings are consistent with previous studies (e.g., Cheng et al. (8); Watson et al. (10)), yet this study uniquely applies the method using real-world data from Afghanistan, offering context-specific insights.

A major strength of the proposed approach is its capacity to accurately reconstruct multi-wave epidemic patterns without the need for manual parameter adjustments. This is facilitated by the dynamic parameter estimation enabled through neural networks and compartment-specific loss functions (4), which improve fitting precision despite missing or noisy data.

However, several limitations remain. First, the model's accuracy is contingent upon the quality and consistency of input data an ongoing challenge in Afghanistan due to underreporting and limited testing (1, 13). Second, training DINNs can be computationally intensive, particularly for large-scale or real-time applications (4).

Traditional compartmental models struggle to capture time-varying transmission due to their reliance on constant parameters. This study acknowledged this challenge in the Introduction and discussed linear parameter-varying (LPV) models as a conceptual solution (11). These models enable dynamic adaptation of transmission parameters and, when incorporated into hybrid frameworks like DINNs, enhance realism and forecasting power.

Importantly, the results from the sensitivity analysis have practical policy implications. For instance, the model shows high sensitivity to changes in the incubation rate (σ), recovery rate (γ), and transmission rate (β). Public health measures that can influence these parameters—such as early testing and isolation (which reduces σ), improved treatment capacity (affecting γ), and social distancing or mask mandates (reducing β)—could substantially alter epidemic outcomes. Therefore, policymakers in Afghanistan should prioritize investments in early detection infrastructure and public communication strategies to modulate these key parameters effectively (9, 10, 22).

Furthermore, incorporating mobility data and seroprevalence surveys in future versions of the model could enhance its accuracy and applicability (18). Bayesian approaches may also be employed to quantify predictive uncertainty, thereby supporting risk-informed decision-making in health policy planning (18, 19).

Conclusion

This study demonstrated the effectiveness of dynamics-informed neural networks (DINNs) integrated with an SEIR-V framework in modeling the spread and vaccination dynamics of COVID-19 in Afghanistan. By embedding the SEIR-V differential equations into the neural network architecture and training the model on real-world epidemiological data, the DINNs approach achieved high prediction accuracy, particularly for the infected and vaccinated compartments, as evidenced by low error metrics and high R^2 scores.

The model's ability to dynamically estimate key parameters—such as transmission, recovery, and vaccination rates—offers a substantial advantage over traditional static models, particularly in data-scarce and under-reported settings like Afghanistan. Moreover, the parameter sensitivity analysis highlights critical intervention points that can inform public health strategies, such as enhancing early detection, accelerating vaccination campaigns, and promoting non-pharmaceutical interventions to reduce transmission.

This research also reinforces the value of incorporating flexible modeling techniques, such as linear parameter-varying (LPV) systems and hybrid physics-informed architectures, to better reflect real-time epidemic dynamics. Future work could benefit from integrating mobility and serological data, as well as employing Bayesian methods to quantify uncertainty in predictions.

Overall, this study underscores the potential of data-driven, dynamics-informed modeling frameworks to support real-time public health decision-making and

epidemic preparedness in low-resource environments.

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