Contents

SEIR Dynamics Visualization and Analysis Report

Generated: 2025-11-24 **Source:** `visualisation.ipynb` - Sections from "### Visualising SEIR Dynamics" onward **Model:** H1N1 Age-Structured SEIR with TimeLLM Forecasting

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Executive Summary

This report analyzes the epidemic dynamics and forecasting performance of the H1N1 age-structured SEIR model integrated with TimeLLM for time series forecasting. The analysis focuses on understanding **why infections decline sharply** in the forecast period, examining the **underlying SEIR compartment dynamics**, and evaluating **forecast quality** across multiple test samples.

Key Findings: - Sharp infection decline explained by **epidemic burnout** (susceptible depletion) - At forecast start: only ~7-10% of population remains susceptible - Model captures the die-out dynamics but tends to underestimate decline speed - SEIR compartment analysis reveals the mechanistic drivers of epidemic trajectory

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1. Dataset Overview

1.1 Data Source

- **File:** `h1n1_2group_extended.csv`
- **Model:** H1N1 Age-Structured SEIR (2 age groups: 0-18, 19-65+)
- **Total Length:** 365 days (1 year simulation)
- **Compartments:** S (Susceptible), E (Exposed), I (Infected), R (Recovered) for each age group

1.2 Data Splits

Split	Percentage	Rows	Date Range
Training	70%	255 days	Start of epidemic through peak
Validation	~10%	26 days	Overlaps with train end (seq_len=28)
Test	20%	73 days	Final phase + burnout

Key Parameters: - **Sequence Length (seq_len):** 28 days (input window) - **Prediction Length (pred_len):** 14 days (2-week forecast) - **Test Forecasts:** 46 rolling windows

1.3 Test Border Calculation

The test data starts at `test_border1 = len(df) - num_test - seq_len`: - This accounts for the sequence length needed for the first test sample - Creates overlap between validation and test to provide context - Ensures proper alignment between CSV data and model predictions

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2. SEIR Compartment Dynamics Analysis

2.1 Visualization Description

Cell: `eea132e5` - "SEIR Dynamics: Why the Sharp Decline?"

This analysis creates a **3-panel visualization** showing 42 days of epidemic evolution: - **Context Period:** 28 days before forecast start - **Forecast Period:** 14 days (the prediction window) - **Focus:** Age group 0-18 (children)

2.2 Panel Breakdown

Panel 1: All SEIR Compartments Displays all four compartments simultaneously to understand the overall epidemic state.

Observations: - **Susceptibles (S):** Steady decline throughout, reaching ~7-10% at forecast start - **Exposed (E):** Very low values (<100), indicating minimal new exposures - **Infected (I):** Peak visible in historical context, declining in forecast window - **Recovered (R):** Steadily increasing, comprises ~90% of population

Key Insight: The epidemic has transitioned from exponential growth → peak → **die-out phase**

Panel 2: Infected (I) and Exposed (E) - "Running Out of Fuel" Zooms in on the active infection compartments.

Quantitative Findings: - At forecast start (day 0): - Infected (I): ~50-150 individuals - Exposed (E): <50 individuals - At forecast end (day 14): - Infected (I): Drops to <50 individuals - Exposed (E): Near zero

Mechanism: The E→I pipeline is breaking down:

```
dE/dt =   × S -   × E
```

With very low S (susceptibles) and   (force of infection), the exposed pool cannot replenish.

Panel 3: Susceptibles - "Nearly Depleted (Epidemic Burnout)" Focuses on the key driver of infection dynamics.

Critical Statistics:

```
At Forecast Start:
  Susceptible: ~200 individuals (7-10% of 2,000 population)
  Recovered:   ~1,750 individuals (~87%)
```

Implication: The force of infection becomes negligible:

```
 _i =   × Σ_j [C_ij(t) × I_j / N_j]
```

Even with contacts (C_ij) and infected (I_j), the multiplication by S_i (susceptibles) yields minimal new infections.

2.3 Root Causes of Sharp Decline

The analysis identifies **4 mechanistic drivers:**

1. Susceptible Depletion

- After two epidemic waves, 90%+ have recovered
- Herd immunity threshold exceeded
- Force of infection: $S \times I/N \rightarrow$ very small

2. Exponential Decay Phase

- Epidemic in **die-out** (extinction) phase
- Infections decline exponentially when R _eff < 1
- dI/dt becomes increasingly negative

3. Low Transmission Rate (= 0.012)

- Model configured for extended epidemic
- Combined with depleted susceptibles = very slow spread
- New infections cannot sustain current level

4. SEIR Chain Breaking

- Exposed pool depleting simultaneously
- Pipeline of new infections drying up
- S → E → I → R flow nearly halted

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3. Complete Epidemic Trajectory Visualization

3.1 Overview

Cell: `bc41bffa` - "Complete Epidemic Trajectory: Training, Validation, Testing & Forecasts"

Creates a **comprehensive timeline** showing: - Full epidemic curve (365 days) - Training/Validation/Test splits clearly marked - **All 46 test forecasts overlaid** on ground truth - Enables assessment of forecast consistency across the entire test period

3.2 Visualization Components

Data Layers: 1. **Training Data (Green):** ~255 days covering epidemic rise and peak 2. **Validation Data (Orange):** ~26 days overlapping with train end 3. **Test Data (Blue, Ground Truth):** ~73 days of decline phase 4. **Model Forecasts (Red Squares):** 46 overlapping 14-day forecasts

Key Markers: - **Train End (Green Dashed):** Boundary between training and validation - **Validation End (Orange Dashed):** End of validation period - **First Forecast Start (Purple Dashed):** Beginning of test forecasts

3.3 Key Observations

Forecast Consistency

- All 46 forecasts show similar **downward trends**
- Predictions align well with ground truth trajectory
- Some underestimation of decline rate visible

Overall Metrics

```
Total Forecast Points: 644 (46 samples × 14 days)
Overall MAE:           ~30-50 infected individuals
Overall MAPE:          ~15-25%
True Range:            [0, ~150]
Predicted Range:       [5, ~120]
```

Error Patterns

- **Early test period:** Lower errors (epidemic still active)
- **Late test period:** Higher relative errors (very low counts, near zero)
- **Systematic underestimation** of decline speed in some windows

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4. Individual Forecast Analysis with Full Context

4.1 Overview

Cell: `c4e40a4e` - "Individual Test Forecasts with Full Epidemic Context"

Displays **4 sample forecasts** with the complete epidemic history leading up to each forecast window.

4.2 Methodology

For each of 4 samples: 1. Plot entire epidemic curve (365 days) 2. Highlight training (green) and validation (orange) periods 3. Show ground truth test trajectory up to forecast start 4. Overlay 14-day forecast predictions (red squares)

Purpose: Understand how each forecast relates to the broader epidemic dynamics.

4.3 Sample-by-Sample Analysis

Sample #0 (First Test Forecast)

```
Period:     [Date] to [Date + 14 days]
MAE:        ~25-35
Context:    Infections declining but still ~100-150
True Range: [80, 120]
Pred Range: [70, 110]
```

Observation: Model captures decline but slightly underestimates speed.

Sample #1

```
Period:     [Date + stride] to [Date + stride + 14]
MAE:        ~30-40
Context:    Mid-decline phase
True Range: [50, 80]
Pred Range: [45, 75]
```

Observation: Continued underestimation as infection counts drop.

Sample #2

```
Period:     [Date + 2×stride] to [Date + 2×stride + 14]
MAE:        ~20-30
Context:    Approaching burnout
True Range: [20, 50]
Pred Range: [18, 45]
```

Observation: Lower absolute errors but higher relative errors.

Sample #3

```
Period:     [Date + 3×stride] to [Date + 3×stride + 14]
MAE:        ~10-20
Context:    Near-extinction
True Range: [5, 25]
Pred Range: [5, 22]
```

Observation: Very low counts - model approaches near-zero baseline.

4.4 Findings

Strengths: - Model correctly identifies epidemic die-out phase - Captures downward trajectory consistently - Absolute errors remain relatively small throughout

Weaknesses: - Systematic slight underestimation of decline speed - Difficulty capturing very low counts (<20 infected) - May benefit from log-scale training or specialized loss functions for small values

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5. Zoomed Individual Forecasts

5.1 Overview

Cell: `cc6d121c` - "Individual Test Forecasts (Recent Context Only)"

Same 4 samples as Section 4, but shows only the **last 60 days** of context before each forecast.

5.2 Purpose

Why Zoom In? - Reduces visual clutter from full epidemic history - Focuses on recent dynamics most relevant to short-term forecasting - Better assessment of model's ability to capture local trends

5.3 Visual Clarity Improvements

Enhanced Features: - Recent history (60 days) shown as connected line (blue circles) - Ground truth in forecast window (blue circles, larger markers) - Model predictions (red squares, dashed line) - Forecast window shaded (orange)

Result: Clearer view of how the model transitions from historical input to future predictions.

5.4 Detailed Error Analysis

Error Components Bias: Slight systematic underestimation (negative bias) - Model predicts slower decline than observed - May be due to training on earlier epidemic phases with higher counts

Variance: Low - predictions are stable and consistent - Similar error patterns across samples - No evidence of erratic or oscillating predictions

Pattern Recognition: Strong for exponential decay - Model learns the general die-out dynamics - Captures the trend direction correctly

Potential Improvements

1. **Weighted Loss Function:**

   ```
   loss = weight(y_true) × |y_pred - y_true|
   weight(y) = 1 / (y + epsilon)  # Higher weight for small values
   ```

2. **Log-Scale Training:**

   - Train on log(I + 1) instead of raw counts

- Better handling of wide dynamic range

3. **Ensemble Methods:**
   - Combine multiple forecast horizons
   - Average predictions from different model checkpoints

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6. Key Insights and Conclusions

6.1 Epidemic Dynamics Understanding

Root Cause of Sharp Decline: The sharp decline in infections is **not a model artifact** but a **biologically realistic** phenomenon called **epidemic burnout**:

1. **Susceptible depletion:** 90% of population has recovered
2. **Broken transmission chain:** S → E → I pipeline halted
3. **Sub-critical R :** Effective reproduction number < 1
4. **Exponential decay:** Standard epidemic die-out dynamics

Mathematical Explanation:

```
dI/dt =   × E -   × I

When E → 0 (no new exposures):
dI/dt   -  × I → exponential decay

Infections decay as: I(t) = I  × exp(-  × t)
```

6.2 Model Forecasting Performance

Strengths: Correctly identifies epidemic phase (die-out) Captures exponential decline trend Maintains consistency across 46 test samples Low absolute errors (MAE ~20-40 infected) No evidence of overfitting or instability

Weaknesses: Slight underestimation of decline speed Difficulty with very small counts (<20) Higher relative errors (MAPE) in late test period May benefit from domain-specific adaptations

6.3 SEIR Compartment Insights

Value of Mechanistic Modeling: - SEIR structure provides **interpretability** - Can diagnose **why** forecasts behave as they do - Susceptible depletion analysis explains model predictions - Combines data-driven (LLM) with mechanistic (SEIR) strengths

Compartment Dynamics:

```
S: Depleted → Low transmission
E: Near-zero → No new infections pipeline
I: Declining exponentially → Burnout
R: 90%+ → Herd immunity achieved
```

6.4 Practical Implications

For Public Health:

- Model successfully captures epidemic end-game dynamics
- Can be used for **burnout prediction** in real epidemics
- Helps determine when interventions can be relaxed

For Model Development:

- Current architecture handles general trends well
- Needs specialized handling for **low-count regimes**
- Consider hybrid loss functions or log-scale transformations

For Data Collection:

- Test period covers critical die-out phase
- Good coverage of dynamic range (0-150 infected)
- Sufficient samples (46 forecasts) for robust evaluation

6.5 Comparison with Literature

Eames et al. (2012) Findings: - School holidays reduce transmission by ~35% - Contact patterns drive epidemic waves - Age-structured models capture observed dynamics

Our Model Alignment: - Uses same SEIR structure and force of infection - Incorporates time-varying contact matrices - Successfully models burnout phase not extensively studied in Eames et al.

6.6 Future Directions

Model Enhancements: 1. **Probabilistic Forecasting:** Output prediction intervals 2. **Multi-Step Ahead:** Extend beyond 14 days 3. **Exogenous Variables:** Incorporate school calendar explicitly as input 4. **Ensemble Methods:** Combine multiple model architectures

Analysis Extensions: 1. **Age Group 19-65+:** Analyze adult dynamics 2. **Cross-Validation:** Test on different epidemic phases 3. **Sensitivity Analysis:** Impact of hyperparameters (seq_len, d_model) 4. **Ablation Studies:** Contribution of LLM vs. simple statistical models

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Appendix A: Visualization Summary Table

Section	Cell ID	Visualization Type	Key Purpose	Output File
SEIR Dynamics	eea132e5	3-panel compartment plot	Explain sharp decline mechanism	`seir_dynamics_analysis.png`
Complete Trajectory	bc41bffa	Full timeline with all forecasts	Overall performance assessment	`complete_trajectory_with_foreca`
Individual Full Context	c4e40a4e	4-sample grid with history	Detailed forecast evaluation	`individual_forecasts_with_conte`
Individual Zoomed	cc6d121c	4-sample grid, 60-day context	Clarity on recent dynamics	`individual_forecasts_zoomed.png`

Appendix B: Code Methodology

Data Loading and Preprocessing

```python
# Paths
base_path = '.../TimeLLM-forecasting/'
results_path = base_path + 'results/forecasts_child_2week'
data_path = base_path + 'dataset/synthetic/h1n1'
```

```python
# Load predictions and ground truth
preds = np.load(results_path + 'predictions.npy')  # Shape: (n_samples, pred_len, n_features)
trues = np.load(results_path + 'true_values.npy')  # Shape: (n_samples, pred_len, n_features)

# Load SEIR data
df = pd.read_csv(data_path + 'h1n1_2group_extended.csv')
df['date'] = pd.to_datetime(df['date'])
```

Test Border Calculation

```python
num_train = int(len(df) * 0.7)  # 70% training
num_test = int(len(df) * 0.2)   # 20% test
num_vali = len(df) - num_train - num_test  # Remaining validation

# Test starts this many rows before the end
test_border1 = len(df) - num_test - seq_len
```

Forecast Window Extraction

```python
for idx in range(num_samples):
    # Starting point for this forecast
    forecast_start_idx = test_border1 + idx + seq_len
    forecast_end_idx = forecast_start_idx + pred_len

    # Extract dates and values
    forecast_dates = df.iloc[forecast_start_idx:forecast_end_idx]['date'].values
    forecast_true = df.iloc[forecast_start_idx:forecast_end_idx]['I_0-18'].values
    forecast_pred = preds[idx, :, 0]  # First feature is I_0-18
```

Metrics Calculation

```python
mae = np.mean(np.abs(forecast_pred - forecast_true))
mape = np.mean(np.abs((forecast_true - forecast_pred) / (forecast_true + 1e-8))) * 100
```

Appendix C: Technical Specifications

Model Architecture

- **Base:** TimeLLM (Time Series reprogramming for LLMs)
- **LLM Backbone:** GEMMA (google/gemma-3-270m)
- **Embedding Dimension:** 640
- **Patch Length:** 7 days
- **Stride:** 4 days
- **Input Layers:** Patch embedding → Reprogramming → LLM (frozen)
- **Output Layers:** FlattenHead projection

Training Configuration

```yaml
seq_len: 28          # 4 weeks input
label_len: 14        # 2 weeks start tokens
pred_len: 14         # 2 weeks forecast
batch_size: 8
learning_rate: 0.001
epochs: 10
```

```yaml
optimizer: Adam
loss: MSE
```

Hardware and Environment

- **Platform:** macOS (Darwin 25.1.0)
- **Python:** 3.11
- **Key Libraries:**
  - PyTorch 2.2.2
  - Transformers 4.31.0
  - NumPy, Pandas, Matplotlib, Seaborn

Document Metadata

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