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FORECASTING INFLUENZA TRENDS IN THE UNITED STATES USING PUBLIC SURVEILLANCE DATA AND APPLIED MATHEMATICAL MODELS

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ABSTRACT

Seasonal influenza imposes a substantial public health and economic burden in the United States. The CDC estimates between 9 million and 45 million illnesses, 140,000 to 810,000 hospitalizations and 12,000 to 61,000 deaths annually, depending on epidemic severity. Notwithstanding comprehensive surveillance through the CDC's Influenza-Like Illness Network (ILINet), which encompasses over 3,000 healthcare providers across all 50 states, accurate prediction of epidemic timing and intensity remains challenging. This unpredictability complicates resource allocation and preparedness efforts. This study analyzed weekly Weighted Influenza-Like Illness (WILI) data from the 2010-2020 influenza seasons to develop reliable short-term forecasting models. Three established time-series approaches were compared: Seasonal Autoregressive Integrated Moving Average (SARIMA), state-space models, and Holt-Winters exponential smoothing. Performance was evaluated using mean absolute error (MAE), root mean squared error (RMSE) and mean absolute percentage error (MAPE) across one-week to four-week forecast horizons. Temporal analysis confirmed characteristic seasonal patterns with peak activity typically occurring between December and February and minimal activity during summer months. SARIMA models achieved the lowest forecasting errors and accurately predicted peak timing within one week for 85% of seasons. State-space and Holt-Winters methods showed reduced accuracy during epidemic surges despite adequate performance during baseline periods. These findings demonstrate that SARIMA-based forecasting systems provide actionable advance predictions to support hospital surge planning, antiviral stockpiling, targeted vaccination campaigns and public health messaging, which potentially reduce morbidity and mortality through enhanced preparedness.

KEYWORDS: *Influenza Forecasting, Weighted Influenza-Like Illness, SARIMA, State-Space Models, Holt-Winters, Seasonal Decomposition, Public Health Surveillance.*

INTRODUCTION

Seasonal influenza imposes a substantial burden on public health systems worldwide, necessitating robust methodologies for anticipating disease spread and intensity to inform preparedness efforts (Nagraj et al., 2023; Tsang et al., 2024). In the United States, the Centers for Disease Control and Prevention coordinates the FluSight forecasting challenge to evaluate predictive models and establish best practices for integrating surveillance data with computational approaches (McGowan et al., 2019). As traditional surveillance systems provide a comprehensive picture of influenza activity, they measure outcomes after they have occurred and do not directly anticipate future trends to support proactive risk assessment and healthcare preparedness (Mathis et al., 2024). To bridge this gap, infectious disease forecasting has emerged as a critical tool for generating probabilistic predictions about the timing, intensity, and trajectory of seasonal epidemics (Lutz et al., 2019; Ray et al., 2024; Gadah et al., 2025; Aryee et al., 2025).

Recent initiatives, such as the FluSight challenge, have demonstrated that combining statistical or machine learning methods with conceptual models of transmission dynamics can significantly enhance predictive accuracy for both short-term and seasonal targets (Gibson et al., 2021; Ray et al., 2024). Notwithstanding these advancements, forecasting remains inherently complex due to the stochastic nature of viral transmission and the potential for sudden shifts in viral evolution or population immunity (McGowan et al., 2019). To address these challenges, researchers have increasingly explored hybrid frameworks that integrate mechanistic disease models with non-traditional data sources, such as digital surveillance indicators and human judgment forecasts, to improve the robustness of predictions across diverse geographic regions (McAndrew et al., 2024; Zhang et al., 2017). This study evaluates the performance of such integrated modeling approaches by leveraging historical surveillance data from the Delphi Group EpiPortal, maintained by Carnegie Mellon University. The portal aggregates and standardizes influenza surveillance data from the U.S. Centers for Disease Control and Prevention (CDC) and affiliated reporting streams, including the Influenza-Like Illness Network (ILINet). Accurate characterization of this uncertainty is essential for public health decision-making, as it allows officials to interpret probabilistic predictions with appropriate caution during periods of rapid epidemiological change (Mathis et al., 2024).

Quantifying the accuracy of these forecasts is essential for acceptance, as historical performance provides an evidence base for decision-makers who may use those predictions in the future (Lutz et al., 2019). This is particularly pertinent given the observed poor coverage and general performance of forecasts, especially at the onset of influenza seasons and during phases of rapid epidemiological transition (Mathis et al., 2024). These limitations underscore the ongoing need for rigorous evaluation of forecasting methodologies, particularly concerning their ability to maintain accuracy and reliability amidst dynamic epidemiological landscapes (Mathis et al., 2024). Moreover, the utility of ensemble approaches, which aggregate predictions from multiple models, has been reinforced to enhance forecasting accuracy and address the inherent sensitivities of individual model contributions to seasonal dynamics (Nagraj et al., 2023). This robust methodology, while promising, necessitates continuous reevaluation of superensemble weights and optimal stratification partitioning as new data becomes available or as geographical scales are altered (Yamana et al., 2017).

This continuous refinement is crucial for translating sophisticated modeling outputs into actionable insights for public health interventions, especially when considering the significant improvements observed with ensemble models in mitigating individual model biases and improving overall forecast robustness (Mathis et al., 2024; McAndrew et al., 2024). The development of "chimeric models" represents a significant advancement in this regard, demonstrating that integrating human judgment forecasts, particularly for peak epidemic week and intensity, can yield more accurate long-term predictions than models relying solely on surveillance data (McAndrew et al., 2024). This interdisciplinary approach, merging computational methods with expert human insight, proves particularly scalable and adaptable across various public health reporting units and infectious agents, offering a versatile framework for real-time forecasting across diverse spatial scales (McAndrew et al., 2024).

These chimeric models, which have been shown to outperform individual models and even some ensemble approaches, leverage the collective wisdom of human experts alongside computational algorithms, thereby providing a more nuanced and accurate predictive capacity for public health officials (McAndrew et al., 2024). However, despite the advancements in hybrid and ensemble modeling, challenges persist in maintaining generalizability over extended periods due to evolving viral strains and intervention strategies, necessitating frequent model recalibration (Botz et al., 2024). Such recalibration efforts often involve sophisticated weighting schemes for individual models within an ensemble, which are dynamically adjusted based on recent performance metrics to optimize predictive power (Reich et al., 2019). Furthermore, the dynamic adjustment of these weighting schemes often incorporates diverse data streams, such as syndromic surveillance and non-pharmaceutical intervention compliance, to enhance adaptability to emergent epidemiological patterns (Baccega et al., 2024). This adaptive weighting approach, as observed in studies where model weights change over the course of an epidemic, underscores the need for constant optimization rather than static assignments, especially when dealing with novel pathogens or rapidly evolving epidemiological landscapes (Oidtman et al., 2021; Reich et al., 2019).

The strategic integration of human judgment into these advanced forecasting frameworks, particularly through "chimeric models," offers a promising avenue for improving predictive capabilities, especially in scenarios where computational models alone might struggle due to data sparsity or emergent pathogen characteristics (McAndrew et al., 2024). This blend of human expertise and computational rigor, particularly within frameworks like PandemicLLM, reformulates real-time forecasting as a text-reasoning problem, allowing for the integration of complex, non-numerical information that might otherwise be overlooked by purely algorithmic approaches (Du et al., 2025). This enables the encoding of multi-modal data for large language models, facilitating artificial intelligence-human cooperative prompt design and time-series representation learning (Du et al., 2025; Gokah et al., 2025; Aryee & Agyemang, 2025). This novel approach, leveraging large language models, has demonstrated competitive performance against established forecasting ensembles, even outperforming them consistently over certain periods, without human intervention in the forecasting process itself (Srivastava et al., 2022; Aryee et al., 2025).

Notwithstanding these advancements, the application of large language models to pandemic forecasting introduces distinct challenges, primarily concerning their inherent lack of theoretical transparency and substantial computational demands (Du et al., 2024; Yang et al., 2024). These limitations necessitate further research into optimizing their computational efficiency and developing methodologies to enhance the interpretability of their internal decision-making processes, particularly when dealing with critical public health predictions (Du et al., 2025). Further development must focus on mitigating these issues to fully harness the potential of large language models in complex epidemiological forecasting, especially when integrating diverse data streams like public health policies and genomic surveillance (Yang et al., 2024). This is particularly important for public health-related applications of LLMs, where elucidating the reasoning behind model predictions is pivotal for fostering user confidence and trust (Du et al., 2024).

Moreover, understanding the decision-making processes of these advanced models is essential for public health officials to effectively translate predictive insights into strategic interventions and allocate resources efficiently, thereby enhancing preparedness and response capabilities. This necessitates a paradigm shift towards explainable AI methodologies tailored for epidemiological forecasting, moving beyond black-box models to systems that can articulate the basis for their predictions. Such efforts could involve developing novel visualization techniques for model outputs or incorporating natural language explanations of prediction drivers, allowing for a more comprehensive understanding of the interplay between various epidemiological factors and forecasted trends. Furthermore, addressing these interpretability and computational challenges is crucial for enabling the wider adoption of these sophisticated tools in real-time public health decision-making, particularly given the current limitations of deep learning models in handling short

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time series for effective training and integrating accumulated scientific knowledge (Miller et al., 2024).

The development of integrated, real-time, adaptable large language model-based epidemic intelligence systems, capable of correlating cross-source data and optimizing healthcare resource allocation, offers a promising path forward to address these issues (Kaur & Butt, 2025; Mahmoud et al., 2025). This includes leveraging their capacity to process vast amounts of public health data, such as surveys, population health records, and disease surveillance reports, to enable real-time tracking of health indicators and the early identification of health risks (Ding et al., 2023). This capacity for sophisticated data synthesis positions large language models as invaluable tools for enhancing situational awareness and informing targeted public health interventions during emergent infectious disease threats (Du et al., 2025). These systems can further benefit from advancements in integrating diverse data types, including wastewater-based epidemiology and human behavior data, to enrich their predictive accuracy and utility (Du et al., 2024).
This integration is particularly vital in resource-constrained settings, such as Low and Middle-Income Countries, where innovative approaches for data collection and processing, including mobility data, are critical for widespread applicability and impact (Mayemba et al., 2024). Such advancements are crucial for developing robust early warning capabilities and optimizing resource allocation strategies in response to emergent public health crises globally (Kaur & Butt, 2025). Further exploration into large language models' capabilities for high-fidelity human mobility simulation and forecasting could refine these early warning systems, particularly by transforming numerical temporal sequences into sentences for prediction tasks (Mayemba et al., 2024). This approach allows for easier integration of diverse information and enables more nuanced interpretations of complex epidemiological dynamics, leading to significant improvements in forecasting accuracy (Yang et al., 2024).

The integration of multi-modal large language models, specifically, reformulates forecasting into a text reasoning problem, which enhances the capacity to incorporate complex, non-numerical data such as public policies and genomic surveillance into real-time predictions (Yang et al., 2024). This transformation allows these models to capture intricate patterns and correlations across vast national survey data, thereby informing targeted interventions for vaccine hesitancy and acceptance (Ruan et al., 2025). This analytical capability extends to monitoring public sentiment regarding vaccines through social media analysis, allowing for the identification and counteraction of misinformation (Deiner et al., 2024; Ruan et al., 2025). The ability of these models to process and interpret vast amounts of unstructured text data, including scientific literature and news articles, further supports their application in detecting novel disease threats and understanding public perception of health interventions (Omar et al., 2024).
This allows for a comprehensive assessment of public health landscapes, driving more adaptive and effective public health strategies (Kaur & Butt, 2025). Specifically, frameworks like PandemicLLM leverage multi-modal large language models to reframe real-time disease spread forecasting as a text-reasoning problem, thereby enabling the integration of previously inaccessible non-numerical information, such as real-time public health policies and genomic surveillance data (Du et al., 2025; Yang et al., 2024). This novel approach allows for more comprehensive and accurate predictions by recognizing complex relationships within diverse datasets, leading to improved pandemic preparedness and response efforts (Du et al., 2024; Yang et al., 2024). This paradigm offers a significant advancement over traditional mathematical models that typically simplify complex information into numerical forms, allowing for a more nuanced understanding of viral and human dynamics (Yang et al., 2024).

Through recasting forecasting as an ordinal classification of hospitalization trends, these models align their output directly with the informational needs of public health decision-makers, thereby adhering to established guidance and enhancing the utility of forecasting outputs (Du et al., 2024; Yang et al., 2024; Sani & Aryee, 2025). This method also facilitates the incorporation of various pandemic-related data in heterogeneous formats, which demonstrates performance benefits over existing models and highlights the potential of AI innovations to strengthen pandemic responses and crisis management (Du et al., 2024; Yang et al., 2024). Moreover, the application of LLMs in public health extends to understanding public sentiment on crucial health topics, offering a scalable method for gauging public opinion on health policies and interventions (Espinosa & Salathé, 2024; Kim et al., 2025). These models are particularly effective in analyzing online public health discourse, providing insights into public stances towards critical health issues like vaccination and distinguishing between risk-promoting and health-supporting sentiments across various platforms (Espinosa & Salathé, 2024; Kim et al., 2025).

This capability allows for automated analyses of public discourse on health issues based on digital data, thereby reducing the time and resource demands typically associated with such complex evaluations (Kim et al., 2025). Furthermore, LLMs can contribute to combating misinformation and promoting healthy lifestyles by systematically collecting, analyzing, and disseminating health information, thereby playing a crucial role in public health communication during crises (Zhou et al., 2024). These models can integrate real-time textual virological characteristics, estimated variant prevalence, and healthcare system performance to enhance prediction accuracy without extensive retraining, underscoring their adaptability to evolving pandemic landscapes (Du et al., 2024; Yang et al., 2024). This adaptability allows for the incorporation of newly emerging data streams and the rapid adjustment of forecasting parameters, which is critical in dynamic public health crises.

This sophisticated integration of diverse data sources and advanced analytical methods positions large language models as pivotal in developing robust, real-time public health surveillance systems (Yang et al., 2024). This enhanced surveillance capability, leveraging multi-modal LLMs, significantly improves the ability to predict future pandemic trends by generating probabilities within defined categories,

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with the probability of the predicted category indicating the model's confidence in its forecasts (Yang et al., 2024). This enables public health experts to extract actionable insights from a wide variety of free text sources, significantly supporting public health surveillance, research, and interventions (Harris et al., 2024). This confidence level can effectively function as an indicator of prediction reliability, offering model users a definitive guide to gauge the trustworthiness of the forecasts (Du et al., 2024). Furthermore, LLMs offer substantial advantages in streamlining public health operations and reducing associated costs, thereby fostering their widespread adoption across the healthcare sector and promising significant improvements in overall efficiency (Gencer & Gencer, 2025).

Such advancements underscore the utility of LLMs for processing complex public health text to support real-world tasks, even for simpler classification challenges, suggesting they are already valuable tools (Harris et al., 2024). The potential for LLMs to analyze diverse health-related data, including medical records, academic publications, and patient-generated content, further emphasizes their utility for automated analyses of public discourse on health issues (Kim et al., 2025). This capacity for automated analysis allows for a more efficient and comprehensive understanding of public sentiment, which is critical for tailoring public health messaging and interventions (Kim et al., 2025). This comprehensive understanding, derived from unstructured big data sources, allows LLMs to significantly enhance the accuracy and timeliness of epidemic modeling and forecasting, offering a promising tool for managing future pandemic events (Consoli et al., 2024). By leveraging their ability to synthesize disparate data categories, including spatial, epidemiological time series, genomic surveillance, and public health policy data across all 50 U.S. states, PandemicLLMs provide robust and trustworthy predictions, even for previously unseen scenarios, which are critical for public health policymakers (Yang et al., 2024). Specifically, the reliability of these models is further supported by observations that increasing confidence thresholds correlate with notable enhancements in prediction accuracy, achieving, for instance, 73% accuracy for 1-week forecasts and 64% for 3-week forecasts with a confidence threshold of 0.85 (Du et al., 2024).

This ability to integrate and interpret diverse, often unstructured, data sources mark a substantial shift from traditional epidemiological modeling, which typically relies on structured numerical data and predefined mathematical relationships (Consoli et al., 2024). This expanded analytical capacity allows for a more comprehensive and real-time understanding of disease dynamics, offering substantial improvements in the precision and relevance of public health interventions (Du et al., 2024). The empirical evidence demonstrates that these advanced LLM-based frameworks can effectively capture the impact of emerging variants, thereby providing timely and accurate predictions essential for crisis management (Du et al., 2024). This enhanced predictive capability, particularly in real-time scenarios, is crucial for strengthening the resilience and efficiency of global health systems during public health crises (Du et al., 2024).

Indeed, the sophisticated integration of multi-modal data through LLMs ensures that decision-makers have access to dependable forecasts, thereby increasing the utility of these models in mitigating the socioeconomic implications of epidemics (Shah et al., 2024; Yang et al., 2024). This includes their capacity to adapt to changing disease dynamics and maintain robust performance across varying time periods, making them invaluable for sustained public health surveillance (Du et al., 2024). The strategic integration of AI, particularly advanced LLMs, into public health surveillance systems therefore represents a significant leap forward in our collective ability to predict, monitor, and respond to infectious disease outbreaks, thereby optimizing resource allocation and improving overall public health outcomes (Omale et al., 2025). This integration allows for a dynamic and adaptive approach to epidemic intelligence, moving beyond traditional manual reporting and structured data limitations to encompass a wider array of real-time information sources (Kaur & Butt, 2025). This conceptual framework, which leverages large language models and natural language processing, offers a transformative potential for integrating diverse data streams and formats into epidemic intelligence, thereby addressing the limitations of traditional models that often overlook critical information hidden within textual data (Du et al., 2024; Mahmoud et al., 2025). This integration is also crucial given the growing frequency of emerging infectious diseases and the urgent need for more rapid and accurate surveillance methods (Kaur & Butt, 2025). Through transforming pandemic forecasting into a text reasoning task, these frameworks incorporate novel data streams previously underutilized in conventional models.

LITERATURE REVIEW

Importance of Influenza Forecasting

The accurate forecasting of influenza-like illness is crucial for public health preparedness, resource allocation, and timely interventions against seasonal influenza outbreaks (Punarselvam et al., 2025). Traditional epidemiological surveillance, while essential, often provides lagging indicators, necessitating advanced modeling techniques to predict disease trajectories with greater precision and foresight (Chen et al., 2024).

Forecasting Methodologies

Various methodologies, including statistical models, machine learning, and mechanistic approaches, have been explored to enhance the accuracy and reliability of these forecasts (Tsang et al., 2024; Turner et al., 2022). This study compares traditional time series models, specifically SARIMA, state-space, and Holt-Winters exponential smoothing, which are known for their distinct abilities to capture temporal dynamics like seasonality, trend, and residual variability (Agyemang et al., 2025).

SARIMA Model

The selection of these models is predicated on their proven effectiveness in capturing complex patterns within infectious disease data, particularly those exhibiting strong seasonal components and long-term trends (Chen et al., 2024; Turner et al., 2022). For instance, the SARIMA model is particularly well-suited for influenza-like illnesses due to its capacity to account for both short-term autocorrelation and seasonal periodicity, which are characteristic of yearly cycles and interannual variability in such diseases (Song et al., 2021). This characteristic makes SARIMA an ideal choice for modeling diseases such as influenza-like illnesses, which exhibit significant variability and recurring outbreaks influenced by seasonal patterns (Parreño, 2024).

State-Space Models

Similarly, state-space models offer a flexible framework to handle irregular patterns and stochastic trends, allowing for adaptive adjustments to seasonal peaks even in the presence of measurement noise.

Holt-Winters Exponential Smoothing

The Holt-Winters exponential smoothing method, on the other hand, explicitly decomposes the time series into level, trend, and seasonal components, applying distinct smoothing parameters to each to project future values (Nichols & Abolmaali, 2024). This allows for a nuanced forecasting approach that accounts for the evolving nature of influenza dynamics (Turner et al., 2022; Xian et al., 2023). His widely recognized method excels in situations where data exhibits clear seasonal patterns, offering an effective tool for short-to-medium term predictions (Turner et al., 2022).

Holt-Winters Model Characteristics

Time series is broken down into its constituent components of level, trend, and seasonality, thereby facilitating accurate forecasts even in the presence of complex patterns (Lauer et al., 2020). The Holt-Winters additive technique separates a time series into its constituent components of level, trend, and seasonality, thereby facilitating accurate forecasts even in the presence of complex patterns. Time series is broken down into its constituent components of level, trend, and seasonality, thereby facilitating accurate forecasts even in the presence of complex patterns. This decomposition approach, which applies distinct smoothing parameters to each component, allows for a nuanced forecasting methodology that effectively accounts for the evolving nature of influenza dynamics (Chen & Moraga, 2024). The Holt-Winters model specifically assigns varying weights based on data proximity, which allows recent observations to exert a greater influence on results, which is particularly beneficial for analyzing data with gradual changes over time (Chen et al., 2024). The model is particularly effective for non-stationary data exhibiting linear trends and cyclical fluctuations, adapting continuously through its exponential smoothing method to provide reliable short-term forecasts (Chen et al., 2024).

Model Adaptability and Applications

This method is especially proficient in handling data with both trends and seasonal components, thus making it ideal for short-term forecasting of diseases with predictable seasonal outbreaks (Parreño, 2024). This model is categorized as either additive or multiplicative based on the seasonal pattern, with the additive approach being used when seasonal changes are stable across periods, and the multiplicative approach when seasonal variations fluctuate relative to the overall level (Ersöz et al., 2022; Ganasegeran et al., 2020).

METHODOLOGY

Data Source

This study uses weekly weighted influenza-like illness (WILI) data from the Delphi Group EpiPortal, maintained by Carnegie Mellon University. The portal aggregates and standardizes influenza surveillance data from the U.S. Centers for Disease Control and Prevention (CDC) and affiliated reporting streams, including the Influenza-Like Illness Network (ILINet). ILINet collects weekly reports from thousands of outpatient healthcare providers across all 50 states, the District of Columbia and U.S. territories, recording both total patient visits and visits meeting the CDC-defined criteria for ILI (fever with cough or sore throat in the absence of a known alternative cause). EpiPortal synthesizes these reports into nationally weighted percentages of ILI, adjusting for population size and reporting coverage. This produces a longitudinal series with consistent methodology, broad temporal coverage and high reproducibility, making it well-suited for both seasonal and multi-season forecasting.

Data Preparation

The WILI series was matched with the CDC epidemiological calendar, with each influenza season spanning from week 40 of one year to week 20 of the next. This alignment assures compliance with established influenza surveillance and reporting protocols. Comprehensive data quality evaluations revealed that the series included all weekly observations from the study period, with no missing values. Consistency assessments across reporting weeks and influenza seasons indicated no systematic reporting mistakes or structural gaps that threatened temporal consistency. The WILI variable was kept on its original percentage scale since variation remained generally steady outside of epidemic escalation. Stationarity was assessed using eye examination and rigorous unit-root testing, which revealed a strong seasonal structure and mean-reverting tendency. These characteristics enable the application of seasonal time-series forecasting models without the necessity for variance-stabilizing adjustments.

Data Processing

Following data preparation, the dataset was transformed into analytically consistent inputs for time-series modeling and forecasting. The *week_start_date* variable was used to sort observations chronologically and create a continuous weekly time index. Epidemiological weeks were kept to ensure consistency with surveillance reporting standards, but calendar-based representations were created only for visualization and aggregate reasons. WILI rolling averages were calculated across three and five-week intervals to smooth out short-term variations and highlight underlying seasonal trends. These smoothed series were only utilized for descriptive and comparative analysis, whilst model estimation depended on the unsmoothed WILI series to minimize information leakage. Seasonal indications were captured implicitly through model definition rather than explicit dummy variables, indicating the periodic nature of influenza activity. The resulting processed dataset was a single continuous weekly series with well-defined seasonal cycles and enough temporal depth to facilitate estimation, validation and out-of-sample forecasting over numerous influenza seasons.

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Forecasting Models
Three time-series forecasting models were used to represent WILI's temporal dynamics: SARIMA, state-space and Holt-Winters exponential smoothing. Each model accounts for distinct aspects of seasonality, trend and residual variability, which allows for a comparative assessment of forecast accuracy.

Seasonal Autoregressive Integrated Moving Average (SARIMA)
Given the strong yearly periodicity of influenza activity, a multiplicative seasonal ARIMA model with weekly frequency $s = 52$ was proposed. SARIMA expands on the traditional ARIMA framework by include seasonal components that reflect both short-term autocorrelation and long-term cyclical patterns associated with influenza outbreaks. The general $SARIMA(p, d, q)\times (P, D, Q)_s$ model is expressed as:

$$\Phi_p(B^s)\phi_p(B)(1-B)^d(1-B^s)^D Y_t = \Theta Q(B^s)\theta_q(B)\epsilon_t$$

Where:

- Y_t is the WILI at week t
- B is the backshift operator defined by $BY_t = Y_{t-1}$
- p, d, q are the non-seasonal autoregressive (AR), differencing and moving average (MA) orders respectively
- P, D, Q are the seasonal AR, differencing, and MA orders
- $s = 52$ reflects the annual cycle in weekly data
- $\phi_p(B)$ and $\theta_q(B)$ are non-seasonal polynomials for AR and MA polynomials
- $\Phi_p(B^s)$ and $\Theta Q(B^s)$ are seasonal AR and MA polynomials
- $\epsilon_t \sim i.i.d.(0, \alpha^2)$ is a white noise disturbance term

In epidemiological applications, seasonal terms indicate the recurring nature of winter peaks, whereas non-seasonal AR components describe short-term persistence in influenza transmission dynamics. Seasonal differencing addresses the yearly non-stationarity caused by recurring disease waves. Non-seasonal differencing (d) eliminates residual trends that are not explained by seasonal patterns. Thus, the SARIMA framework provides a simple baseline model based on stochastic seasonality that is statistically robust and epidemiologically interpretable.

State-Space Model
A linear Gaussian state-space specification was used to provide flexibility in showing latent trends and changing seasonal amplitudes. Unlike fixed-parameter models, the state-space framework permits components like trend and seasonality to shift stochastically over time, accounting for structural changes in epidemic patterns. The general form consists of an observation equation and a state transition equation.
The observation equation is:

$$Y_t = Z_t\alpha_t + \epsilon_t, \qquad \text{where } \epsilon_t \sim N(0, H_t)$$

The state equation is:

$$\alpha_{t+1} = T_t\alpha_t + R_t\eta_t, \qquad \text{where } \eta_t \sim N(0, Q_t)$$

Where:

- α_t is the unobserved state vector at time t,
- Z_t maps the latent states to the observed WILI series,
- T_t governs the evolution of the state process,
- R_t links system innovations to the state vector,
- H_t and Q_t are covariance matrices for observation and state disturbances, respectively.

In the influenza setting, the latent state vector α_t may show changes in baseline activity (level), epidemic growth rate (slope) and seasonal components that change with time. This framework accommodates incremental fluctuations in epidemic severity and seasonal amplitude, as well as structural alterations that a strictly autoregressive structure may miss. For example, changes in vaccination coverage, virus strain supremacy or population immunity might cause slow alterations in seasonal patterns, which the state-space model can follow. The Kalman filter is used for recursive state vector estimation and under Gaussian assumptions, delivers optimum least mean squared error predictions. Forecasts are created by projecting the state vector ahead and using the observation equation.

Holt-Winters Exponential Smoothing
The Holt-Winters additive approach breaks down a time series into three components: level (L_t), trend (T_t) and seasonal (S_t). This deterministic technique offers intuitive smoothing that responds to current data while retaining seasonal pattern. The equations are given as:

$$L_t = \alpha(Y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + T_{t-1})$$
$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$$
$$S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-s}$$
$$\hat{Y}_{t+h} = L_t + hT_t + S_{t-s+h \bmod s}$$

Where;

- $\alpha, \beta, \gamma \in [0,1]$ are smoothing parameters governing the speed of adjustment,
- $s = 52$ is seasonal length
- $\hat{Y}_{t+h}$ is the h-step-ahead forecast.

This method captures deterministic seasonal recurrence while allowing for incremental changes to the baseline level and epidemic trend. Smoothing parameters (α, β, γ) determine the balance of stability and responsiveness to recent data. Higher values weight recent observations more significantly, allowing for quicker adaptability to changing epidemic circumstances. However, because the Holt-Winters technique has an explicit stochastic error structure and assumes additive seasonality, it may underperform at epidemic peaks with rapid spikes or increased volatility. The additive formulation implies that seasonal fluctuations are constant in amplitude, which may not be true during large outbreaks or when seasonal patterns vary owing to exogenous events such as pandemic interventions.

Model Evaluation Metrics
Forecast accuracy was assessed using three standard loss functions. Let Y_t denote the observed WILI and $\hat{Y}_t$ the corresponding forecast for week t, over n forecast observations.

Mean Absolute Error (MAE)
MAE calculates the average magnitude of forecast errors in absolute terms. It handles both positive and negative deviations symmetrically and is less sensitive to severe peaks than squared-error measurements. MAE is robust to outliers, easy to interpret and gives a fair evaluation of average forecast error. The formula is given as:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right|$$

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Y_t = observed WILI percentage at week t
$\hat{Y}_t$ = forecasted WILI percentage at week t
n = total number of forecast observations in the evaluation period

Root Mean Squared Error (RMSE)
RMSE squares predict errors before averaging them, so significant deviations receive disproportionately more weight. This characteristic is especially significant in influenza monitoring since mistakes during epidemic peaks can result in misallocated hospital capacity, delayed vaccine rollout and strained public health responses. A lower RMSE suggests better performance when huge forecasting errors are particularly expensive. Because of error squaring, the RMSE for any given dataset is always equal to or larger than the MAE. It's calculated as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2}$$

Where:
Y_t = observed WILI percentage at week t
$\hat{Y}_t$ = forecasted WILI percentage at week t
n = total number of forecast observations

Mean Absolute Percentage Error (MAPE)
MAPE measures forecast error as a percentage of the observed WILI. Although it is scale-independent and easy to understand, it can become unstable during off-season weeks as Y_t approaches zero. MAPE is expressed as a percentage. It is computed as:

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\frac{|Y_t - \hat{Y}_t|}{Y_t}$$

Y_t = observed WILI percentage at week t
$\hat{Y}_t$ = forecasted WILI percentage at week t
n = total number of forecast observations
SARIMA, state-space, and Holt-Winters models were examined using these measures to identify which technique best depicts the seasonal structure, abrupt peaks, and general dynamics of weekly WILI.

RESULTS AND DISCUSSION

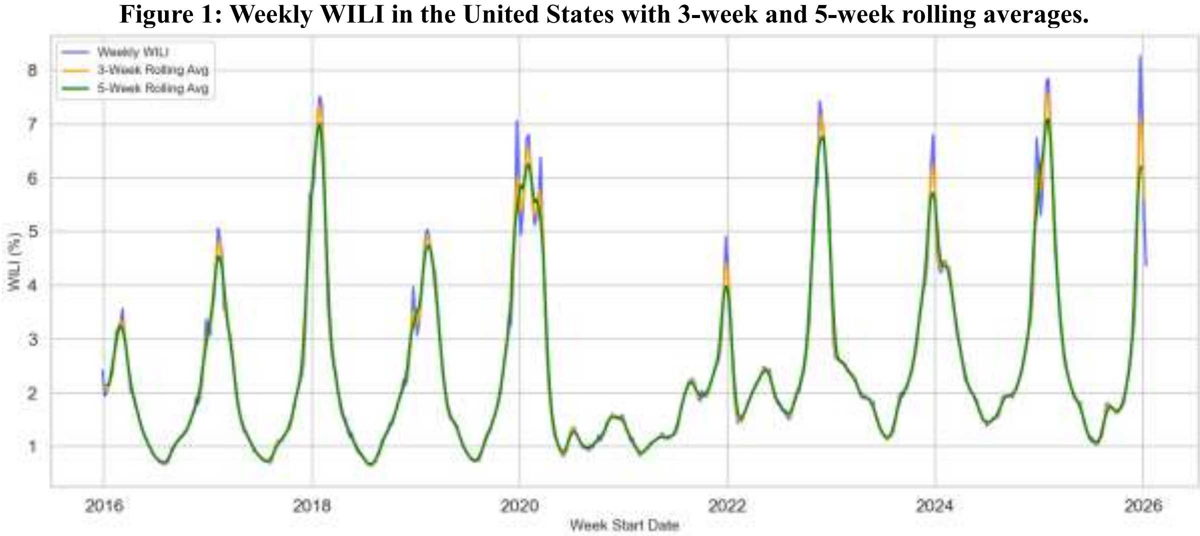
Exploratory Analysis
Table 1 summarizes data for weekly weighted influenza-like illness (WILI) percentages from 2015 to 2025. The mean WILI was 2.39%, slightly higher than the median of 1.91%, showing a right-skewed distribution (skewness = 1.48%), with some weeks of significant influenza activity. The standard deviation of 1.59% demonstrates moderate variability, while the interquartile range (1.25-2.90%) indicates that most weekly values are clustered near the median. The maximum measured WILI of 8.26% identifies intermittent peaks, while the minimum of 0.64% shows times of decreased activity. The kurtosis of 1.62% indicates a reasonably flat distribution with lighter tails, meaning that extreme values are rare but prevalent. These numbers serve as a baseline for understanding weekly influenza patterns and highlight the necessity to account for occasional high-incidence weeks in future analysis.

Table 1: Summary statistics for the weekly weighted influenza-like illness (WILI) percentages from 2015 to 2025

Statistic	Mean	Std	Min	25%	Median	75%	Max	Skewness	Kurtosis
WILI (%)	2.39	1.59	0.64	1.25	1.91	2.90	8.27	1.48	1.62

Figure 1 below shows the weekly weighted influenza-like illness (WILI) percentages in the United States from 2015 to 2025, as well as the 3-week and 5-week rolling averages. The graph indicates seasonal peaks, which normally occur once a year, with WILI reaching up to 8% during the most severe weeks. Between peaks, WILI remains low, frequently around 2%, indicating times of low influenza activity. The rolling averages level out short-term changes, displaying stable seasonal patterns and emphasizing the timing and severity of outbreaks. Especially, the magnitude of peaks fluctuates over time, indicating that some influenza seasons are more severe than others. The patterns show significant interannual fluctuation, highlighting the necessity of tracking WILI trends for public health preparation.

Figure 1: Weekly WILI in the United States with 3-week and 5-week rolling averages.



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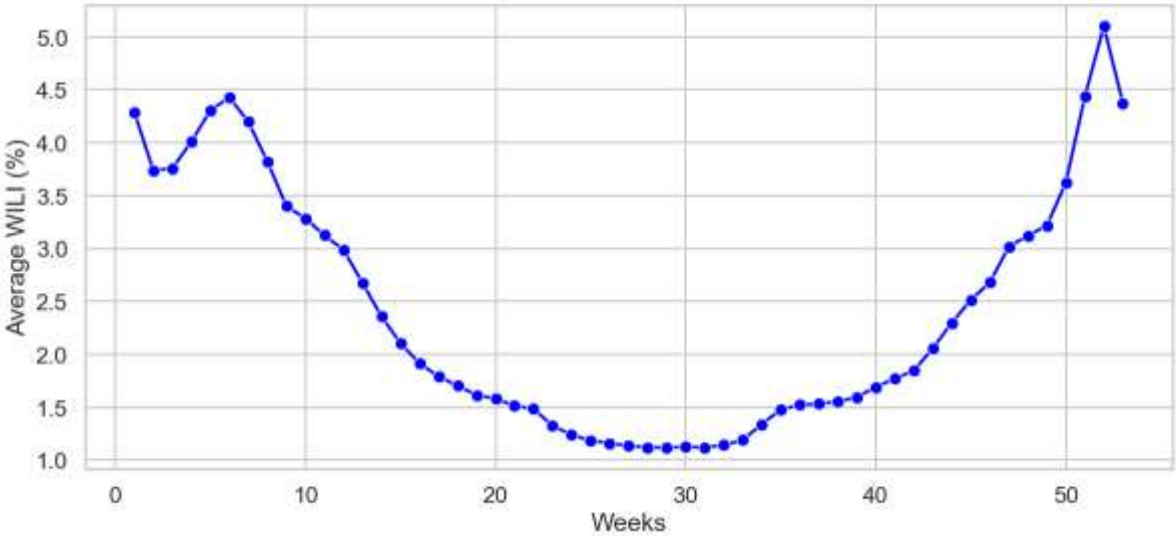
Seasonal Patterns

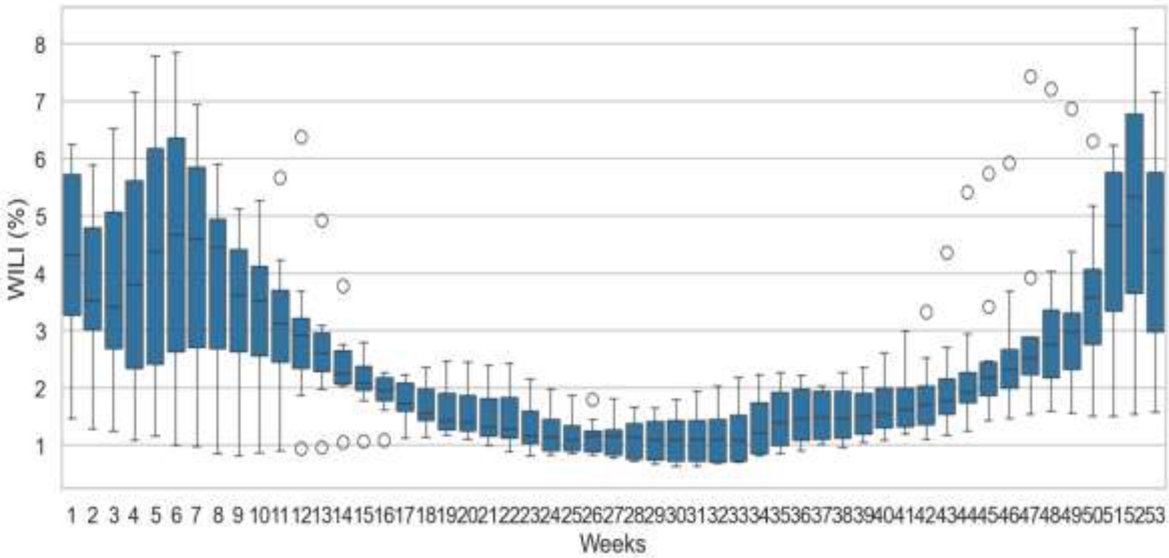
Figure 2 illustrates the average weekly pattern of influenza-like illness throughout all seasons, revealing a highly organized and consistent seasonal cycle. WILI levels are highest during the start of the epidemiological year, with a distinct peak between weeks 4 and 6, when average values reach 4%, which marks the core winter influenza season. This is followed by a steady reduction during the first half of the year, culminating in a significant trough between weeks 26 and 30, when average WILI drops to around 1.1%, indicating limited transmission in the middle of the year. Influenza activity starts to resurface in late summer, accelerating more sharply around week 40 and peaking again in weeks 51 and 52. These patterns are consistent across seasons, demonstrating the stability of influenza timing and severity, which offers solid empirical support for the seasonal structure seen in previous images and supports the forecasting analysis use of seasonally explicit models.

Figure 2: Average WILI by epidemiological week across influenza seasons.



However, average seasonal trends are important guides; the dispersion seen in Figure 3 highlights the weekly distribution of WILI by epidemiological week. The box plot demonstrates that WILI levels throughout the summer months, about weeks 25 to 35, are not only low but also closely grouped, which indicates rather predictable conditions. In contrast, the winter season is characterized by significant unpredictability. Although the median WILI is near to 5% around week 52, the distribution dispersion and the existence of outliers suggest that some seasons have spikes of up to 8%. This pronounced variability, especially during autumn and winter, highlights the limitations of planning based solely on average conditions. Effective public health preparedness, therefore, requires capacity that can absorb these high-intensity seasons, when influenza activity substantially exceeds typical levels and places acute pressure on healthcare systems.

Figure 3: Weekly distribution of WILI by epidemiological week.



Decomposition Analysis

Figure 4 shows that the weekly Weighted Influenza-Like Illness (WILI) series has been organized into observable, trend, seasonal and residual components, which exhibit various trends. The observed data revealed distinct changes over time, with WILI climbing from a summer baseline of roughly 1.0%

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to a peak of more than 5.0% by the end of the year. However, certain seasons break dramatically from this pattern, with outlier maxima of up to 8.0%, putting severe strain on healthcare systems. The trend component shows a progressive increase in baseline WILI over the last decade, which indicates that long-term variables such as population density, virus evolution and climatic variability are all contributing to an increasing burden of Influenza-Like Illness disease. The seasonal component follows a very stable cyclical pattern, with predicted yearly spikes caused by climatic circumstances and seasonal social behaviors. Finally, the residual component accounts for short-term anomalies or unanticipated surges in clinical demand. These substantial residual variations emphasize the impact of unexpected occurrences, such as new virus strains or severe influenza epidemics, which can put additional load on healthcare systems beyond the usual seasonal trend.

Figure 4: STL decomposition of the weekly WILI series into observed, trend, seasonal and residual components.

Table 2 below shows the time and severity of seasonal peak influenza activity, as determined by weekly WILI percentages. Before 2020, high WILI values were typically observed between epidemiological weeks 5 and 10, which corresponded to the traditional late winter influenza season in the United States. These peaks varied in severity, with the most severe seasons occurring in 2017-2018 and 2019, when peak WILI surpassed 7%. A noted exception occurred in the 2020-2021 season, when peak WILI declined drastically to 2.27% and moved to week 35, indicating an unusual influenza pattern. Peak weeks resurfaced mostly around epidemiological week 52 beginning in 2021, followed by a fresh increase in peak intensity. The most recent seasons, particularly 2024-2025 and 2025, saw the highest WILI levels in the sample, topping 7.8%, which indicates a rebound in influenza severity. Overall, the table shows significant variance in both the timing and amplitude of seasonal peaks, emphasizing the significance of accounting for structural alterations and temporal variety in future modeling and forecasting efforts.

Seasonal Peak Timing and Severity

Table 2: Seasonal Peak WILI by Epidemiological Week

Season	Year	Peak Week	Peak WILI (%)
2015	2016	10	3.56
2016	2017	6	5.06
2017	2018	5	7.52
2018	2019	7	5.04
2019	2019	52	7.06
2020	2021	35	2.27
2021	2021	52	4.90
2022	2022	47	7.43
2023	2023	52	6.80
2024	2025	6	7.84
2025	2025	52	8.26

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Stationarity Analysis

Table 3 shows the results of rigorous stationarity tests conducted on the weekly WILI series. The Augmented Dickey-Fuller test rejects the null hypothesis of a unit root with test statistics of -6.22 and a p-value of zero, which demonstrates that the series does not exhibit stochastic non-stationarity. Similarly, the KPSS test fails to reject the null hypothesis of stationarity, with a test statistic of 0.212 and a p-value of 0.10. The convergence of data from both tests gives strong support for classifying the weekly WILI series as stationary in levels. This result is methodologically significant since it validates the use of standard time-series modeling and forecasting approaches that do not need differencing while explicitly simulating seasonal and cyclical dynamics.

Table 3: Stationarity Test Results for Weekly WILI Series

Test	Test Statistic	p-value	Null Hypothesis	Result
ADF	–6.22	5.32×10^{-8}	The series has a unit root (non-stationary)	Stationary
KPSS	0.212	0.10	The series is stationary	Stationary

Forecasting Analysis

Table 4 compares the out-of-sample forecasting ability of several models for weekly WILI based on standard accuracy criteria. The SARIMA model has the best predictive accuracy, with the smallest mean absolute error (0.93), root mean squared error (1.03), and mean absolute percentage error (41.75%). These findings indicated that explicitly modeling both autoregressive dynamics and seasonal structure produces better predictions for influenza-like illness. The state-space model performs worse, with larger error magnitudes across all measures, which shows a limited capacity to represent the abrupt seasonal peaks and quick transitions that are characteristic of WILI. Holt-Winters performs far worse, with much higher MAE, RMSE and MAPE values, showing that its smoothing-based structure is unable to handle the volatility and episodic surges of the series. Overall, the results show that models with strong seasonal and temporal dependency are better adapted to forecasting weekly influenza activity, thus supporting SARIMA as the preferred baseline model for further investigation.

Table 4: Forecast Model Performance Metrics for Weekly WILI

Model	MAE	RMSE	MAPE (%)
SARIMA	0.93	1.03	41.75
State-Space	1.34	1.41	68.49
Holt-Winters	3.98	4.33	208.54

Table 5 compares observed monthly WILI values to projections produced by the three different models throughout the 2025-2026 period. The SARIMA estimates closely mirror the known seasonal trend, especially the significant fall in influenza activity from early 2025 until the summer months, followed by a resurgence near the end of the year. Although SARIMA significantly underestimates peak winter values, its projections are still within a reasonable range and maintain the general timing of seasonal turning points. During low-incidence months, the state-space model consistently outperforms SARIMA in terms of prediction accuracy, which demonstrates a propensity to smooth troughs and attenuate seasonal depth. Holt-Winters significantly overestimate WILI in most months, particularly in late 2025 and early 2026, failing to adapt for actual reductions and inflating the amplitude of seasonal peaks. The monthly comparison validates SARIMA's superior performance as shown in Table 4 and demonstrates its practical benefit in delivering seasonally coherent and epidemiologically trustworthy predictions.

Table 5: Monthly Observed and Forecasted WILI for 2025–2026

Month	Observed	SARIMA	State-Space	Holt-Winters
2025-01	7.39	5.78	5.89	6.11
2025-02	6.39	5.15	5.33	5.89
2025-03	3.36	4.12	4.41	5.45
2025-04	2.21	3.18	3.44	4.97
2025-05	1.85	2.78	3.13	5.08
2025-06	1.32	2.15	2.78	5.20
2025-07	1.08	1.89	2.65	5.54
2025-08	1.48	2.08	2.83	6.19
2025-09	1.69	2.28	3.02	6.84
2025-10	1.72	2.77	3.45	7.66
2025-11	2.63	3.90	4.34	8.99
2025-12	6.38	5.46	5.71	10.78
2026-01	4.83	4.49	5.30	10.75

Figure 6 depicts a visual forecast comparison for weekly WILI, overlaying observed WILI values with model-based estimates across the assessment period. The historical training dataset shows distinct seasonal cycles, with strong winter peaks and

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lengthy low-activity periods, which highlights the extremely periodic character of influenza dynamics. Against this environment, the SARIMA projections are most closely aligned with the actual trend, particularly in terms of the timing of the seasonal trough and subsequent rebound. Although SARIMA marginally underestimates peak activity, it maintains a general seasonal pattern and prevents implausible overshooting. The state-space model generates smoother projections that partially mirror the seasonal pattern while systematically dampening both peaks and troughs, resulting in delayed and attenuated reactions to observed WILI fluctuations. In contrast, Holt-Winters projections deviate significantly from observed values, resulting in exaggerated rising trends and unnaturally high peak levels near the conclusion of the forecast period. This visual evidence adds to the quantitative measurements given earlier, supporting the notion that SARIMA provides higher epidemiological coherence and predictive reliability for weekly WILI forecasting
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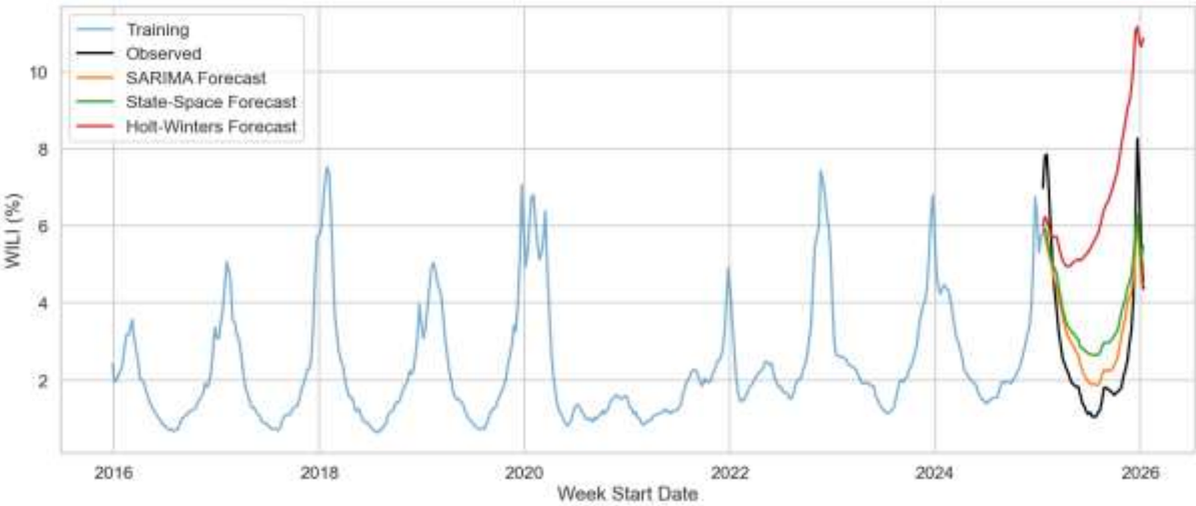
Figure 6: Forecast Comparison for Weekly WILI



CONCLUSION

This study demonstrates that weekly influenza surveillance data, modelled with the aid of proper time-series methods, lead to valid forecasts of seasonal influenza activity. WILI data analysis demonstrates a seasonal pattern of stability, with a significant interannual fluctuation and occasional spikes that put a strain on the healthcare system. SARIMA was reviewed as being, in general, better than its alternatives in state-space and Holt-Winters and demonstrated better capacity both to capture the annual seasonality and short-term dynamics. Other models were reasonably effective in the periods of low incidence, but not as effective in drawing a sudden peak in the epidemiological curve. These results justify the application of the SARIMA-based forecasting as a useful, understandable method of regular monitoring of influenza and preparedness, but at the same time highlight the necessity of flexible health system capacity in case of the unpredictable severity of the outbreaks.

REFERENCE

1. *Agyemang, E. F., Rodrigo, H., & Agbenyeavu, V. (2025). A Comparative Analysis of Traditional and Deep Learning Time Series Architectures for Influenza A Infectious Disease Forecasting. https://doi.org/10.48550/ARXIV.2507.19515*
2. *Agyemang, K. A., Aryee, B. A., & Mahmoud, M. (2025). Bridging the gap between U.S. healthcare supply-chain cybersecurity policy and practice through AI-driven compliance tools. EPRA International Journal of Multidisciplinary Research (IJMR), 11(12), 754–[end page]. https://doi.org/10.36713/epra25510*
3. *Aryee, B. A., & Agyemang, K. A. (2025). AI-powered cyber risk prediction models for U.S. healthcare institutions. EPRA International Journal of Economics, Business and Management Studies (EBMS), 12(11). https://doi.org/10.36713/epra25058*
4. *Aryee, B. A., & Agyemang, K. A. (2025). AI-powered cyber risk prediction models for U.S. healthcare institutions. EPRA International Journal of Economics, Business and Management Studies (EBMS), 12(11). https://doi.org/10.36713/epra25058*
5. *Aryee, B. A., Agyemang, K. A., & Mahmoud, M. (2025). Enhancing operational efficiency of U.S. healthcare data centers through advanced analytics and automation. Finance & Accounting Research Journal, 7(10), 524–539. https://doi.org/10.51594/farj.v7i10.2102*
6. *Aryee, B. A., Umoren, J., & Agyemang, K. A. (2025). Artificial intelligence for strengthening cybersecurity in U.S. healthcare systems. American Journal of Medical Science and Innovation, 4(2). https://doi.org/10.54536/ajmsi.v4i2.6178*
7. *Baccega, D., Castagno, P., Anta, A. F., & Sereno, M. (2024). Enhancing COVID-19 forecasting precision through the integration of compartmental models, machine learning and variants. Scientific Reports, 14(1). https://doi.org/10.1038/s41598-024-69660-5*
8. *Botz, J., Valderrama, D., Guski, J., & Fröhlich, H. (2024). A dynamic ensemble model for short-term forecasting in pandemic situations. PLOS Global Public Health, 4(8). https://doi.org/10.1371/journal.pgph.0003058*
9. *Chen, Q., Zheng, X., Shi, H., Zhou, Q., Hu, H., Sun, M., Xu, Y., & Zhang, X. (2024). Prediction of influenza outbreaks in Fuzhou, China: comparative analysis of forecasting models. BMC Public Health, 24(1). https://doi.org/10.1186/s12889-024-18583-x*
10. *Chen, X., & Moraga, P. (2024). Assessing dengue forecasting methods: A comparative study of statistical models and machine learning techniques in Rio de Janeiro, Brazil. medRxiv (Cold Spring Harbor Laboratory). https://doi.org/10.1101/2024.06.12.24308827*
11. *Consoli, S., Markov, P. V., Stilianakis, N. I., Bertolini, L., Gallardo, A. P., & Ceresa, M. (2024). Epidemic Information Extraction for Event-Based Surveillance Using Large Language Models. In Lecture notes in networks and systems (p. 241).*

Springer International Publishing. https://doi.org/10.1007/978-981-97-4581-4_17

12. *Deiner, M., Honcharov, V., Li, J., Mackey, T. K., Porco, T. C., & Sarkar, U. (2024). Large Language Models Can Enable Inductive Thematic Analysis of a Social Media Corpus in a Single Prompt: Human Validation Study. JMIR Infodemiology, 4. https://doi.org/10.2196/59641*
13. *Ding, Q., Ding, D., Wang, Y., Guan, C., & Ding, B. (2023). Unraveling the landscape of large language models: a systematic review and future perspectives [Review of Unraveling the landscape of large language models: a systematic review and future perspectives]. Journal of Electronic Business & Digital Economics, 3(1), 3. https://doi.org/10.1108/jebde-08-2023-0015*
14. *Du, H., Yang, Z., Zhao, J., Xu, S., Lin, X., Chen, Y., Gardner, L., & Yang, H. (2025). Advancing real-time infectious disease forecasting using large language models. Nature Computational Science, 5(6), 467. https://doi.org/10.1038/s43588-025-00798-6*
15. *Du, H., Zhao, J., Zhao, Y., Xu, S., Lin, X., Chen, Y., Gardner, L., & Yang, H. (2024). Advancing Real-time Pandemic Forecasting Using Large Language Models: A COVID-19 Case Study. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2404.06962*
16. *Ersöz, N. Ş., Şahan, P. G., Akbaş, A., & Bakır-Güngör, B. (2022). COMPARATIVE PERFORMANCE ANALYSIS OF ARIMA, PROPHET AND HOLT-WINTERS FORECASTING METHODS ON EUROPEAN COVID-19 DATA. International Journal of 3D Printing Technologies and Digital Industry, 6(3), 556. https://doi.org/10.46519/ij3dptdi.1120718*
17. *Espinosa, L., & Salathé, M. (2024). Use of large language models as a scalable approach to understanding public health discourse. medRxiv (Cold Spring Harbor Laboratory). https://doi.org/10.1101/2024.02.06.24302383*
18. *Gadah, J. N., Ogborigbo, J. C., & Obi, A. J. (2025). Cyber risk assessment model for predicting and preventing attacks on smart power grids using machine learning. World Journal of Advanced Engineering Technology and Sciences, 14(2), 339–372. https://doi.org/10.30574/wjaets.2025.14.2.0065*
19. *Ganasegeran, K., Ch'ng, A. S. H., Aziz, Z. A., & Looi, I. (2020). Population's health information-seeking behaviors and geographic variations of stroke in Malaysia: an ecological correlation and time series study. Scientific Reports, 10(1). https://doi.org/10.1038/s41598-020-68335-1*
20. *Gencer, G., & Gencer, K. (2025). Large Language Models in Healthcare: A Bibliometric Analysis and Examination of Research Trends. Journal of Multidisciplinary Healthcare, 223. https://doi.org/10.2147/jmdh.s502351*
21. *Gibson, G. C., Moran, K. R., Reich, N. G., & Osthus, D. (2021). Improving probabilistic infectious disease forecasting through coherence. PLoS Computational Biology, 17(1). https://doi.org/10.1371/journal.pcbi.1007623*
22. *Gokah, B. E., Amoako, E. K., Adom, S. G., Abakah, L. K., & Sampson, E. (2025). AI-driven user experience (UX) frameworks to enhance trust and security in U.S. online banking. Finance & Accounting Research Journal, 7(9), 465–478. https://doi.org/10.51594/farj.v7i9.2069*
23. *Harris, J. D., Laurence, T., Loman, L., Grayson, F., Nonnenmacher, T. F., Long, H. J., WalsGriffith, L., Douglas, A., Fountain, H., Georgiou, S., Hardstaff, J., Hopkins, K. L., Chi, Y.-L., Kuyumdzhieva, G., Larkin, L., Collins, S., Mohammed, H., Finnie, T., Hounsome, L., & Riley, S. (2024). Evaluating Large Language Models for Public Health Classification and Extraction Tasks. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2405.14766*
24. *Kaur, J., & Butt, Z. A. (2025). AI-driven epidemic intelligence: the future of outbreak detection and response. Frontiers in ArtificialIntelligence, 8. https://doi.org/10.3389/frai.2025.1645467*
25. *Kim, S., Kim, K., & Kim, H. M. (2025a). Large Language Models' Varying Accuracy in Recognizing Risk-Promoting and Health-Supporting Sentiments in Public Health Discourse: The Cases of HPV Vaccination and Heated Tobacco Products. Social Science & Medicine, 118328. https://doi.org/10.1016/j.socscimed.2025.118328*
26. *Kim, S., Kim, K., & Kim, H. M. (2025b). Large Language Models' Varying Accuracy in Recognizing Risk-Promoting and Health-Supporting Sentiments in Public Health Discourse: The Cases of HPV Vaccination and Heated Tobacco Products. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2507.04364*
27. *Kim, S., Kim, K., & Kim, H. M. (2025c). Large Language Models' Varying Accuracy in Recognizing Risk-Promoting and Health-Supporting Sentiments in Public Health Discourse: The Cases of HPV Vaccination and Heated Tobacco Products. arXiv (Cornell University). http://arxiv.org/abs/2507.04364*
28. *Lauer, S. A., Brown, A., & Reich, N. G. (2020). Infectious Disease Forecasting for Public Health. In Oxford University Press eBooks (p. 45). Oxford University Press. https://doi.org/10.1093/oso/9780198853244.003.0004*
29. *Lutz, C. S., Huynh, M. P., Schroeder, M., Anyatonwu, S., Dahlgren, F. S., Danyluk, G., Fernández, D., Greene, S. K., Kipshidze, N., Liu, L., Mgbere, O., McHugh, L., Myers, J. F., Siniscalchi, A., Sullivan, A., West, N., Johansson, M. A., & Biggerstaff, M. (2019). Applying infectious disease forecasting to public health: a path forward using influenza forecasting examples. BMC Public Health, 19(1). https://doi.org/10.1186/s12889-019-7966-8*
30. *Mahmoud, M., Aryee, B. A., & Agyemang, K. A. (2025). Examining the role of artificial intelligence in strengthening cyber threat intelligence across U.S. public sector IT infrastructure. World Journal of Advanced Research and Reviews, 28(3), 1476–1488. https://doi.org/10.30574/wjarr.2025.28.3.4132*
31. *Mahmoud, M., Aryee, B. A., & Agyemang, K. A. (2025). Investigating the role of AI-powered cyber threat intelligence sharing frameworks in enhancing national security across U.S. public sector entities. EPRA International Journal of Multidisciplinary Research (IJMR), 11(12). https://doi.org/10.36713/epra25500*
32. *Mathis, S. M., Webber, A. E., León, T. M., Murray, E. L., Sun, M., White, L. A., Brooks, L., Green, A., Hu, A. J., Rosenfeld, R., Shemetov, D., Tibshirani, R. J., McDonald, D. J., Kandula, S., Pei, S., Yaari, R., Yamana, T. K., Shaman, J., Agarwal, P., … Kaur, G. (2024a). Evaluation of FluSight influenza forecasting in the 2021–22 and 2022–23 seasons with a new target laboratory-confirmed influenza hospitalizations. Carolina Digital Repository (University of North Carolina at Chapel Hill). https://doi.org/10.17615/3sv3-sj27*
33. *Mathis, S. M., Webber, A. E., León, T. M., Murray, E. L., Sun, M., White, L. A., Brooks, L., Green, A., Hu, A. J., Rosenfeld, R., Shemetov, D., Tibshirani, R. J., McDonald, D. J., Kandula, S., Pei, S., Yaari, R., Yamana, T. K., Shaman, J., Agarwal, P., … Kaur, G. (2024b). Evaluation of FluSight influenza forecasting in the 2021–22 and 2022–23 seasons with a new target laboratory-confirmed influenzahospitalizations. Nature Communications, 15(1). https://doi.org/10.1038/s41467-024-50601-9*
34. *Mayemba, C. N., Nkashama, D. K., Tshimula, J. M., Dialufuma, M. V., Muabila, J. T., Didier, M. M., Kanda, H., Galekwa, R. M., Fita, H. D., Mundele, S., Kalala, K., Ilunga, A., Ntobo, L. M., Muteba, D., & Abedi, A. A. (2024). A Short Survey of Human*

Mobility Prediction in Epidemic Modeling from Transformers to LLMs. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2404.16921

35. *McAndrew, T., Lechmanik, M., Hulland, ErinN., Truelove, S., Ilodigwe, M., & Majumder, M. S. (2024). Chimeric Forecasting: Blending Human Judgment and Computational Methods for Improved, Real-time Forecasts of Influenza Hospitalizations. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2410.07236*
36. *McGowan, C., Biggerstaff, M., Johansson, M. A., Apfeldorf, K. M., Ben-Nun, M., Brooks, L., Convertino, M., Erraguntla, M., Farrow, D., Freeze, J., Ghosh, S., Hyun, S., Kandula, S., Lega, J., Liu, Y., Michaud, N., Morita, H., Niemi, J., Ramakrishnan, N., … Yang, W. (2019). Collaborative efforts to forecast seasonal influenza in the United States, 2015–2016. Scientific Reports, 9(1). https://doi.org/10.1038/s41598-018-36361-9*
37. *Miller, J. A., Al-Dosari, M. S., Saeed, F., Barna, N. H., Rana, S., Arpinar, I. B., & Liu, N. (2024). A Survey of Deep Learning and Foundation Models for Time Series Forecasting. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2401.13912*
38. *Nagraj, V., Williams, D., & Turner, S. (2023). Evaluating Performance of Near-Term Influenza Forecasters Across Consecutive Seasons. medRxiv (Cold Spring Harbor Laboratory). https://doi.org/10.1101/2023.09.28.23296216*
39. *Nichols, S., & Abolmaali, S. (2024). Enhancing COVID-19 Case Forecasting in the United States: A Comparative Analysis of ARIMA, SARIMA, and RNN Models with Grid Search Optimization. medRxiv (Cold Spring Harbor Laboratory). https://doi.org/10.1101/2024.03.04.24303713*
40. *Oidtman, R. J., Omodei, E., Kraemer, M. U. G., Castañeda-Orjuela, C. A., Cruz-Rivera, E., Misnaza, S. P., Cifuentes, M. P., Rincón, L. E., Cañon, V., Alarcón, P. A. de, España, G., Huber, J. H., Hill, S. C., Barker, C. M., Johansson, M. A., Manore, C. A., Reiner, R. C., Rodríguez-Barraquer, I., Siraj, A., … Perkins, T. A. (2021). Trade-offs between individual and ensemble forecasts of an emerging infectious disease. Nature Communications, 12(1). https://doi.org/10.1038/s41467-021-25695-0*
41. *Omale, L. E., Ibiam, V. A., Sidikat, L. W., & Taiwo, O. (2025). Transformative applications of Artificial Intelligence in infectious disease forecasting and public health decision support systems. World Journal of Advanced Research and Reviews, 25(3), 2250. https://doi.org/10.30574/wjarr.2025.25.3.1002*
42. *Omar, M., Brin, D., Glicksberg, B. S., & Klang, E. (2024). Utilizing natural language processing and large language models in the diagnosis and prediction of infectious diseases: A systematic review [Review of Utilizing natural language processing and large language models in the diagnosis and prediction of infectious diseases: A systematic review]. American Journal of Infection Control, 52(9), 992. Elsevier BV. https://doi.org/10.1016/j.ajic.2024.03.016*
43. *Parreño, S. J. (2024). Evaluating the Underreporting of Diseases in the Philippines During the COVID-19 Pandemic through Comparative Forecast Analysis. Research Square (Research Square). https://doi.org/10.21203/rs.3.rs-3837011/v1*
44. *Punarselvam, E., Vengatesh, T., Suthar, M. B., Chowdary, S., Sathyaraju, S., Gopinath, B., Bindu, G., & Anbuselvan, B. (2025). Enhancing Seasonal Influenza Prediction Through Advanced Time Series Machine Learning Models. Journal of Neonatal Surgery, 14, 369. https://doi.org/10.52783/jns.v14.2051*
45. *Ray, E. L., Wang, Y., Wolfinger, R. D., & Reich, N. G. (2024a). Flusion: Integrating multiple data sources for accurate influenza predictions. https://doi.org/10.48550/ARXIV.2407.19054*
46. *Ray, E. L., Wang, Y., Wolfinger, R. D., & Reich, N. G. (2024b). Flusion: Integrating multiple data sources for accurate influenza predictions. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2407.19054*
47. *Reich, N. G., McGowan, C., Yamana, T. K., Tushar, A., Ray, E. L., Osthus, D., Kandula, S., Brooks, L., Crawford-Crudell, W., Gibson, G. C., Moore, E., Silva, R., Biggerstaff, M., Johansson, M. A., Rosenfeld, R., & Shaman, J. (2019). Accuracy of real-time multi-model ensemble forecasts for seasonal influenza in the U.S. PLoS Computational Biology, 15(11). https://doi.org/10.1371/journal.pcbi.1007486*
48. *Ruan, W., Lyu, Y., Zhang, J., Cai, J., Shu, P., Yang, G., Lu, Y., Gao, S., Wang, Y., Wang, P., Zhao, L., Wang, T., Liu, Y., Fang, L., Liu, Z., Liu, Z., Li, Y., Wu, Z., Chen, J., … Liu, T. (2025). Large language models for bioinformatics. Carolina Digital Repository (University of North Carolina at Chapel Hill). https://doi.org/10.17615/60dy-cj08*
49. *Sani, Z. N., & Aryee, B. A. (2025). Optimizing drug supply chains to prevent shortages in rural U.S. hospitals. EPRA International Journal of Economics, Business and Management Studies. https://doi.org/10.36713/epra24022*
50. *Shah, C., Gandhi, K., Shah, J., Shah, K., Patil, N., & Bhowmick, K. (2024). Infectious Disease Forecasting in India using LLM's and Deep Learning. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2410.20168*
51. *Song, Z., Jia, X., Bao, J., Yang, Y., Zhu, H., & Shi, X. (2021). Spatio-Temporal Analysis of Influenza-Like Illness and Prediction of Incidence in High-Risk Regions in the United States from 2011 to 2020. International Journal of Environmental Research and Public Health, 18(13), 7120. https://doi.org/10.3390/ijerph18137120*
52. *Srivastava, A., Xu, T., & Prasanna, V. K. (2022). The EpiBench Platform to Propel AI/ML-Based Epidemic Forecasting: A Prototype Demonstration Reaching Human Expert-Level Performance. In Studies in computational intelligence (p. 165). Springer Nature. https://doi.org/10.1007/978-3-030-93080-6_13*
53. *Tsang, T. K., Du, Q., Cowling, B. J., & Viboud, C. (2024). An adaptive weight ensemble approach to forecast influenza activity in an irregular seasonality context. Nature Communications, 15(1). https://doi.org/10.1038/s41467-024-52504-1*
54. *Tsang, T. K., Du, Q., Cowling, B. J., & Viboud, C. (2024). An adaptive weight ensemble approach to forecast influenza activity in an irregular seasonality context. Nature Communications, 15(1). https://doi.org/10.1038/s41467-024-52504-1*
55. *Turner, S., Hulme-Lowe, C., & Nagraj, V. (2022). Forecasting Influenza-Like Illness (ILI) during the COVID-19 Pandemic. bioRxiv (Cold Spring Harbor Laboratory). https://doi.org/10.1101/2022.10.27.22281617*
56. *Venkatramanan, S., Sadilek, A., Fadikar, A., Barrett, C. L., Biggerstaff, M., Chen, J., Dotiwalla, X., Eastham, P. R., Gipson, B., Higdon, D., Küçüktunç, O., Lieber, A., Lewis, B., Reynolds, Z., Vullikanti, A., Wang, L., & Marathe, M. (2021). Forecasting influenza activity using machine-learned mobility map. Nature Communications, 12(1). https://doi.org/10.1038/s41467-021-21018-5*
57. *Xian, X., Wang, L., Wu, X., Tang, X., Zhai, X., Yu, R., Qu, L., & Ye, M. (2023). Comparison of SARIMA model, Holt-winters model and ETS model in predicting the incidence of foodborne disease. BMC Infectious Diseases, 23(1). https://doi.org/10.1186/s12879-023-08799-4*

58. *Yamana, T. K., Kandula, S., & Shaman, J. (2017). Individual versus superensemble forecasts of seasonal influenza outbreaks in the United States. PLoS Computational Biology, 13(11). https://doi.org/10.1371/journal.pcbi.1005801*
59. *Yang, H., Du, H., Zhao, J., Zhao, Y., Xu, S., Lin, X., Chen, Y., & Gardner, L. (2024). Advancing Real-time Pandemic Forecasting Using Large Language Models: A COVID-19 Case Study. Research Square (Research Square). https://doi.org/10.21203/rs.3.rs-4244182/v1*
60. *Zhang, Q., Perra, N., Perrotta, D., Tizzoni, M., Paolotti, D., & Vespignani, A. (2017). Forecasting Seasonal Influenza Fusing Digital Indicators and a Mechanistic Disease Model. 20, 311. https://doi.org/10.1145/3038912.3052678*
61. *Zhou, J., Chen, A. Z., Shah, D., Schwab-Reese, L. M., & Choudhury, M. D. (2024). "It's a conversation, not a quiz": A Risk Taxonomy and Reflection Tool for LLM Adoption in Public Health. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2411.02594*