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Mathematical Modeling of Influenza Epidemic Dynamics using Fractional-Order SEIR Equations with IoT-Enabled Biosensors and AI-based Biotechnology for Real-Time Outbreak Prediction

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ABSTRACT: Influenza remains a major public health concern because of its rapid transmission, seasonal variation, and potential to cause widespread outbreaks. Accurate and timely prediction of influenza dynamics is essential for effective disease surveillance, healthcare resource allocation, and early intervention. This study proposes a hybrid mathematical modeling framework that integrates fractional-order Susceptible–Exposed–Infectious–Recovered (SEIR) equations, Internet of Things (IoT)-enabled biosensors, and artificial intelligence (AI)-based forecasting techniques for real-time influenza outbreak prediction. The fractional-order SEIR model incorporates memory effects and nonlocal temporal dependencies to represent the complex progression of influenza more flexibly than conventional integer-order epidemic models. IoT-enabled sensing technologies are considered for continuous collection of relevant physiological and epidemiological information, while AI techniques are employed to identify nonlinear patterns and improve short-term forecasting. The proposed hybrid framework combines

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mechanistic epidemic predictions with AI-based residual correction to enhance predictive performance. Model effectiveness will be assessed by comparing the classical SEIR, fractional-order SEIR, standalone AI, and hybrid SEIR–AI approaches using evaluation metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and outbreak peak prediction error. The framework also incorporates sensitivity analysis and an early-warning mechanism to support timely public health decisions. The proposed study is expected to provide a flexible and data-driven approach to influenza surveillance and outbreak forecasting. Its practical performance will depend on the availability of reliable epidemiological data, sensor validation, and rigorous testing across different influenza seasons and populations.

1. INTRODUCTION

Mathematical Modeling of Influenza Epidemic Dynamics Using Fractional-Order SEIR Equations with IoT-Enabled Biosensors and AI-Based Biotechnology for Real-Time Outbreak Prediction.Influenza is a highly contagious respiratory disease that continues to be a major public health concern because of its rapid transmission, seasonal recurrence, and potential to cause severe illness among vulnerable populations. Seasonal influenza affects millions of people worldwide and places considerable pressure on healthcare systems, particularly during periods of increased transmission. The continuous evolution of influenza viruses, changes in population immunity, and variations in human contact patterns make the prediction and control of influenza outbreaks challenging. The World Health Organization (WHO) emphasizes the importance of surveillance, laboratory diagnosis, and timely reporting to monitor influenza activity and support effective public health interventions [1]. However, conventional surveillance systems primarily depend on clinical diagnosis, laboratory-confirmed cases, hospital admissions, and periodic reporting. These methods may introduce delays between the occurrence of infections and the identification of an emerging outbreak. Therefore, the development of advanced mathematical models integrated with real-time sensing technologies and artificial intelligence (AI) has become an important research direction for improving influenza surveillance and outbreak prediction.

Mathematical modeling provides a systematic approach to understanding infectious disease transmission and evaluating the effectiveness of preventive measures. Among the established epidemiological approaches, the susceptible–exposed–infectious–recovered (SEIR) model is widely used to represent the progression of individuals through different stages of infection. In this model, the population is divided into four compartments: susceptible individuals (\(S\)), exposed individuals (\(E\)), infectious individuals (\(I\)), and recovered individuals (\(R\)). Susceptible individuals may become exposed through contact with infectious individuals, after which they progress to the infectious stage and eventually recover. Hethcote [2] discussed the mathematical foundations of infectious disease models and their applications to epidemic analysis. Murray [3] also presented mathematical techniques for investigating biological systems and disease transmission. Although the classical SEIR model provides a useful foundation for analyzing epidemic dynamics, its integer-order differential equations may not adequately capture all the temporal dependencies and memory effects associated with complex disease processes. This limitation motivates the investigation of fractional-order differential equations as an extension of conventional epidemiological models. Fractional calculus generalizes ordinary differentiation and integration to non-integer orders and provides a mathematical framework for representing systems with memory-dependent behavior. Unlike classical differential equations, fractional-order equations can incorporate the influence of previous states into the current evolution of a system. Diethelm [4] presented a comprehensive treatment of fractional differential equations, including their theoretical foundations and numerical solutions. Caputo and Fabrizio [5] subsequently introduced a fractional derivative formulation with a nonsingular exponential kernel, providing an alternative approach to describing memory-dependent processes. These developments have encouraged the application of fractional calculus in biological and epidemiological research. In influenza modeling, replacing the first-order derivatives of the classical SEIR system with fractional-order derivatives may provide additional flexibility in representing disease progression and transmission patterns. González-Parra et al. [6] investigated a fractional-order epidemic model for simulating influenza A (H1N1) outbreaks, demonstrating the relevance of fractional calculus to influenza dynamics. Nevertheless, the selection of the fractional derivative, its order, and its epidemiological interpretation must be supported by mathematical analysis and empirical validation.

The integration of Internet of Things (IoT)-enabled biosensors provides an additional opportunity to improve influenza surveillance by facilitating the rapid collection and transmission of biological measurements. Biosensors are analytical devices designed to detect specific biological targets, including viral antigens, nucleic acids, and other biomarkers associated with infectious diseases. When connected to IoT networks, these devices can transmit measurements to computational platforms for processing, visualization, and further analysis. Gopinath et al. [6] explored the potential of IoT-supported biosensing for respiratory virus monitoring, highlighting the relevance of combining biosensing technologies with computational approaches. In an influenza surveillance framework, biosensor measurements can complement conventional epidemiological information, including laboratory-confirmed cases, influenza-like illness reports, hospitalization records, and environmental observations. However, reliable implementation requires sensor calibration, laboratory validation, secure data transmission, and appropriate management of missing or noisy observations. The integration of biosensing and epidemiological data may improve the timeliness of outbreak detection and provide additional information for monitoring changes in infection patterns.

Artificial intelligence and machine learning have also demonstrated potential for forecasting infectious disease activity using historical and real-time data. These techniques can identify nonlinear relationships between influenza incidence, environmental conditions, population mobility, and other relevant variables. Machine-learning methods, including random forests, support vector regression, gradient boosting, and long short-term memory networks, can be employed to predict future infection trends and identify potential epidemic peaks. Cheng et al. [7] developed and validated an ensemble machine-learning approach for real-time influenza-like illness forecasting in Taiwan, demonstrating the usefulness of combining multiple data sources for epidemiological prediction. Ray et al. [8] presented an ensemble forecasting approach that integrates multiple influenza surveillance signals to improve influenza prediction. These studies support the use of AI as a complementary tool for epidemic forecasting. Nevertheless, the accuracy of AI-based predictions depends on the quality, representativeness, and availability of the training data. Therefore, model performance should be assessed using independent datasets and established metrics, such as mean absolute error (MAE), root mean square error (RMSE), and prediction error across different forecasting horizons.

Despite these developments, an important research opportunity remains in integrating fractional-order epidemic equations, IoT-enabled biosensors, and AI-based prediction within a unified framework. Fractional-order mathematical models can represent the temporal evolution of infection, IoT-enabled biosensors can provide additional biological observations, and AI algorithms can analyze incoming data to estimate outbreak trends. In the proposed framework, the fractional-order SEIR model describes transitions between susceptible, exposed, infectious, and recovered populations. The model parameters can be estimated or updated using available surveillance data, while an AI component can generate short-term forecasts and identify possible increases in transmission. Biosensor observations can serve as supplementary inputs where validated measurements are available. The framework should also account for reporting delays, measurement uncertainty, and changes in population behavior to ensure reliable predictions. Accordingly, this study proposes a hybrid mathematical and computational framework for influenza epidemic analysis and real-time outbreak prediction. The principal objectives are to formulate a fractional-order SEIR model, investigate its mathematical properties, integrate suitable IoT-enabled biosensor measurements with epidemiological surveillance data, and develop an AI-based prediction mechanism for estimating influenza incidence and identifying potential outbreak periods. The model's performance will be evaluated against a classical integer-order SEIR model and appropriate statistical or machine-learning baselines. Through this integration, the study aims to provide a mathematically grounded approach to influenza surveillance and early warning, supporting timely public health planning and evidence-based intervention strategies.

2. LITERATURE REVIEW

The development of influenza epidemic modeling has progressed from classical compartmental differential equations to fractional-order mathematical systems, intelligent biosensing technologies, and AI-based forecasting methods. The following literature review examines these developments chronologically and identifies the research gap relevant to the proposed study, Mathematical Modeling of Influenza Epidemic Dynamics Using Fractional-Order SEIR Equations with IoT-Enabled Biosensors and AI-Based Biotechnology for Real-Time Outbreak Prediction. During the 1970s, mathematical modeling became an important tool for understanding infectious disease transmission, epidemic thresholds, and population-level disease dynamics. Hoppensteadt and Waltman (1970) investigated the mathematical properties of epidemic models, contributing to the theoretical foundations of compartmental modeling. The subsequent development of susceptible–infectious–recovered (SIR) and susceptible–exposed–infectious–recovered (SEIR) frameworks enabled researchers to represent different stages of

infection and analyze how diseases spread through populations. The SEIR structure is particularly relevant to influenza because it incorporates an exposed compartment representing the latent stage between infection and infectiousness. During the 1980s, researchers increasingly investigated the geographical spread of influenza and the role of population movement in epidemic transmission. Rvachev and Longini (1985) developed a mathematical model for the global spread of influenza, illustrating the importance of international transportation and interconnected populations in understanding large-scale epidemics. Their work established a foundation for examining how localized outbreaks may develop into widespread epidemics through travel and population interactions. During the 1990s, mathematical epidemiology expanded toward more realistic representations of population structure, transmission rates, immunity, and intervention strategies. These developments demonstrated that mathematical models could support public health planning, although their predictive accuracy depended strongly on the availability of reliable epidemiological observations and suitable model assumptions. From 2000 onward, mathematical epidemic modeling became more systematic, with greater emphasis on model stability, reproduction numbers, parameter estimation, and intervention analysis. Hethcote (2000) provided a comprehensive review of infectious disease mathematics, explaining how compartmental models can be adapted to different diseases according to their transmission mechanisms and epidemiological characteristics. These developments encouraged the extension of classical SEIR models to accommodate additional factors, including vaccination, quarantine, age structure, and variations in transmission rates. Such extensions are important for influenza because seasonal changes, population immunity, and viral characteristics influence epidemic behavior. Fractional calculus subsequently attracted attention as a mathematical technique for describing systems with memory-dependent behavior. In contrast to ordinary differential equations, fractional-order equations incorporate nonlocal temporal effects through their derivative operators. This feature motivated researchers to explore fractional epidemic models that could provide more flexible descriptions of disease progression. However, fractional derivatives do not automatically improve epidemiological predictions; their value must be demonstrated through appropriate parameter estimation and comparisons with classical models. The growing interest in fractional-order approaches therefore established a mathematical foundation for investigating influenza transmission beyond conventional integer-order SEIR equations. Between 2015 and 2020, research on fractional-order epidemic models expanded, particularly in response to the need for flexible mathematical descriptions of complex infectious disease dynamics. González-Parra et al. (2014) had already investigated a fractional-order epidemic model for influenza A (H1N1), demonstrating the relevance of fractional differential equations to influenza outbreak simulation. Their work provides a direct connection between fractional calculus and the disease considered in the present study.

Abdullah et al. (2017) investigated analytical and numerical techniques for a fractional temporal SEIR model of measles. Although their study focused on measles rather than influenza, it contributed computational techniques relevant to solving fractional compartmental epidemic equations. During this period, the development of numerical approximation methods and parameter estimation techniques became increasingly important because fractional differential equations often require more computational effort than their integer-order counterparts. Researchers consequently began examining how fractional-order models could be calibrated against observed epidemic data and used to evaluate disease-control strategies.

The influenza A (H1N1) pandemic and subsequent public health challenges also highlighted the need for models that could represent changing transmission patterns and support timely intervention planning. Nevertheless, many mathematical studies continued to rely on aggregated case reports and assumed transmission parameters, limiting their ability to capture rapidly changing conditions. These limitations motivated further research into data-driven parameter estimation, real-time surveillance, and the integration of mathematical models with computational forecasting techniques. From 2021 to 2024, epidemic modeling increasingly incorporated machine learning, data integration, and digital surveillance to improve the analysis of infectious disease patterns. Chen et al. (2021) reviewed fractional epidemic models, including fractional SIR, SEIR, and SEIAR systems, and discussed parameter estimation and numerical methods for fitting models to real epidemic data. Their review identified the importance of combining mathematical formulation with reliable computational methods for epidemic prediction. This research is particularly relevant to the proposed study because it provides a foundation for integrating fractional-order SEIR equations with data-driven forecasting methods. Cheng et al. (2020) developed and validated an ensemble machine-learning approach for real-time influenza-like illness forecasting in Taiwan. Their study demonstrated the potential of combining multiple surveillance sources to improve influenza forecasting. The findings support the use of AI algorithms alongside mechanistic epidemic models, particularly when epidemiological observations are incomplete or transmission patterns are nonlinear. AI-based methods can learn patterns from historical case counts and other explanatory variables, whereas mathematical compartmental models

explicitly represent the movement of individuals between disease states. Combining these approaches may provide a more comprehensive framework for understanding and predicting influenza epidemics.

In parallel, developments in connected sensing technologies created opportunities for collecting biological measurements and transmitting them for computational analysis. Gopinath et al. (2022) examined IoT-supported biosensing approaches for respiratory virus monitoring, illustrating the potential of combining biosensor technologies with connected data systems. These technologies could complement conventional surveillance by providing additional measurements relevant to pathogen detection. However, biosensor readings should not be interpreted as direct measures of population-level infection incidence without suitable validation and epidemiological calibration. Consequently, the integration of biosensing data with fractional-order SEIR models requires careful consideration of measurement reliability, data transmission delays, and the relationship between sensor observations and the underlying disease compartments. Research during this period also emphasized the importance of model validation, uncertainty assessment, and responsible interpretation of forecasting results. Mechanistic models and machine-learning methods have complementary strengths: the former describe disease transmission processes, while the latter identify complex statistical patterns. This complementary relationship provides the motivation for developing an integrated influenza prediction framework. Recent research has focused on integrating mathematical epidemic models with data analytics, computational forecasting, and multiple surveillance sources. Ray et al. (2025) presented Flusion, an ensemble forecasting approach that combines multiple influenza surveillance signals for improved prediction. This work highlights the importance of integrating complementary data streams rather than relying on a single source of epidemiological information. Morris (2025) also reviewed developments in infectious disease modeling, emphasizing statistical methods, network-based approaches, machine learning, data integration, and the continuing challenges of parameter estimation and model validation. A systematic and critical review published by Biyagui et al. (2026) examined 279 studies on fractional-order models of infectious diseases, including influenza, COVID-19, HIV/AIDS, Ebola, and Zika. The review reported that compartmental models, particularly extended SEIR formulations, dominated the literature. It also identified important methodological concerns involving the biological interpretation of fractional parameters, dimensional consistency, and validation against classical models. These findings indicate that future fractional epidemic models should be developed not merely to obtain better numerical fits, but to provide interpretable and testable representations of disease dynamics. In 2026, the integration of AI-assisted forecasting with fractional-order epidemic systems and connected biosensing technologies remains a promising research direction. A recent study comparing seasonal autoregressive integrated moving average (SARIMA) and long short-term memory (LSTM) methods for forecasting laboratory-confirmed influenza detections in South Africa illustrates the continued interest in comparing conventional time-series techniques with deep-learning approaches. Such comparisons are important when determining whether a complex hybrid model provides meaningful improvements over simpler alternatives. The reviewed literature reveals three major research directions: classical compartmental epidemic modeling, fractional-order mathematical modeling, and AI-assisted surveillance and forecasting. Although each direction has contributed significantly to influenza research, several challenges remain. Classical SEIR models provide interpretable representations of infection progression but may not capture all temporal dependencies. Fractional-order models offer additional mathematical flexibility, yet their advantages require careful biological interpretation and empirical validation. AI-based forecasting can identify complex patterns in epidemiological data, but its performance depends on data quality, model selection, and the ability to adapt to changing transmission conditions. IoT-enabled biosensors offer opportunities for supplementary biological monitoring, although their integration with population-level epidemic models requires validated relationships between sensor outputs and epidemiological variables.

Therefore, the principal research gap is the need to investigate a unified framework that combines fractional-order SEIR equations, IoT-enabled biosensor observations, and AI-based forecasting while retaining mathematical interpretability and rigorous validation. The present study addresses this gap by proposing a hybrid modeling approach for influenza epidemic dynamics and real-time outbreak prediction. Its contribution will be evaluated through comparisons with classical SEIR and suitable machine-learning baselines, using epidemiological data, validated sensor measurements where available, and standard forecasting metrics. This approach aims to support more timely influenza surveillance and evidence-based public health decision-making.

3. CONTRIBUTION OF STUDY

Development of a Fractional-Order SEIR Model: Formulate a fractional-order Susceptible–Exposed–Infectious–Recovered (SEIR) mathematical model to analyze influenza transmission dynamics, incorporating memory effects and disease progression.

Integration of IoT-Enabled Biosensors: Incorporate validated IoT-enabled biosensor measurements and real-time surveillance data to support continuous influenza monitoring and timely detection of changes in infection patterns. AI-Based Outbreak Prediction: Develop an AI-based forecasting model using suitable machine-learning or deep-learning algorithms to predict influenza incidence, identify potential outbreak peaks, and estimate short-term transmission trends. Mathematical Analysis and Model Validation: Investigate positivity, boundedness, equilibrium points, stability conditions, and the basic reproduction number. Validate the proposed model using available epidemiological data and assess prediction accuracy using MAE, RMSE, and other relevant performance metrics. Comparative Evaluation and Early-Warning Framework: Compare the proposed hybrid model with classical integer-order SEIR models and standalone AI forecasting methods. Develop an integrated early-warning framework to support timely public health interventions, resource allocation, and influenza outbreak management

3.1.Proposed Methodology

The proposed study integrates a fractional-order SEIR epidemic model, IoT-enabled biosensors, and AI-based forecasting to analyze influenza transmission and support real-time outbreak prediction. The methodology consists of data acquisition, preprocessing, mathematical modeling, AI-based prediction, model validation, and early-warning generation.

3.2. Proposed Work Diagram

The following flow diagram illustrates the overall structure of the proposed framework.

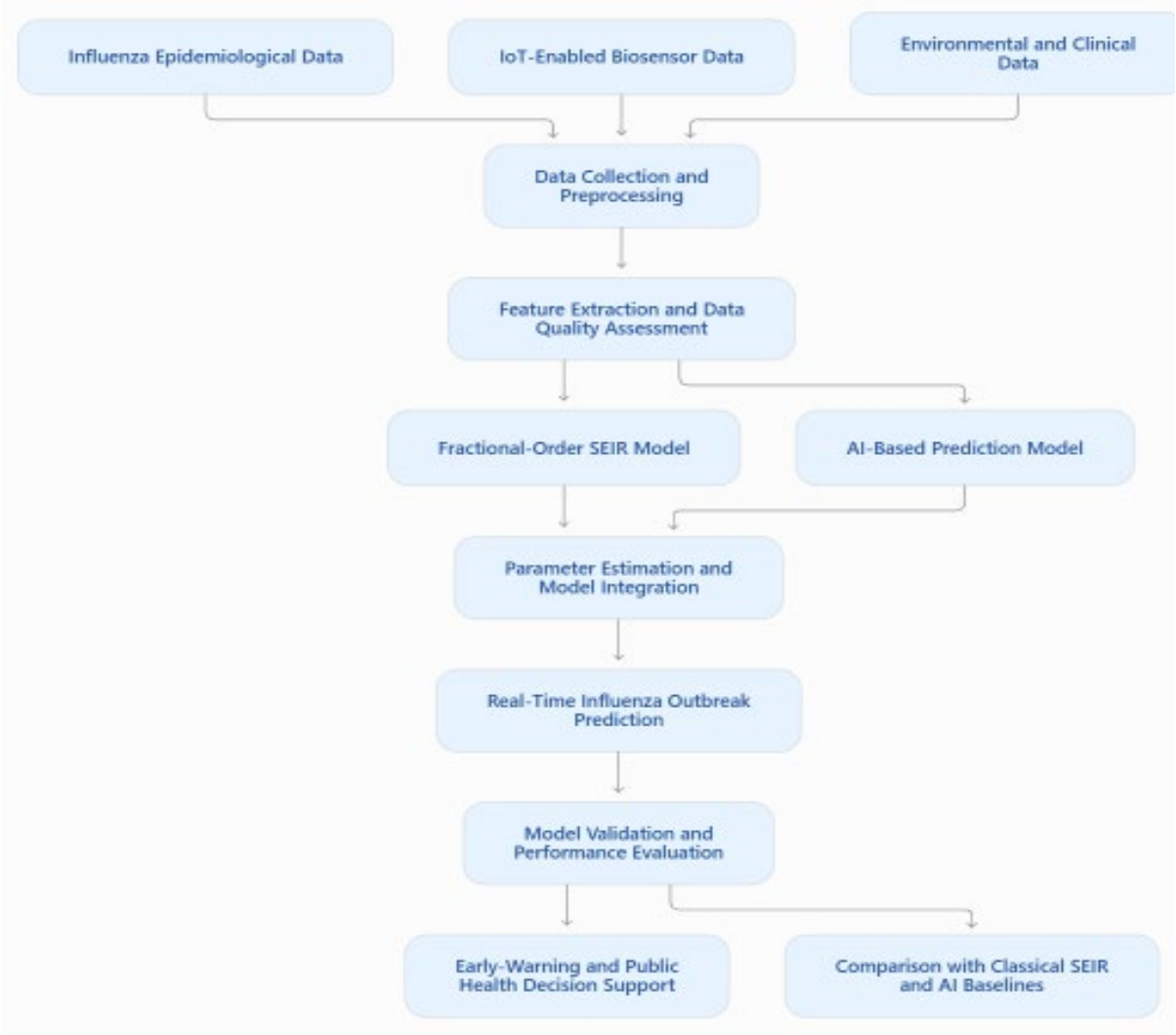


Figure 1. Proposed integrated framework for influenza epidemic prediction using fractional-order SEIR equations, IoT-enabled biosensors, and artificial intelligence.

3.3. Data Collection and Preprocessing

The first stage collects historical influenza case counts, laboratory-confirmed infections, hospitalization records, and other available epidemiological observations. IoT-enabled biosensors may provide validated viral biomarker measurements, while environmental data, such as temperature and humidity, can be incorporated as supplementary predictors when relevant. Data can be obtained from public health surveillance sources and validated experimental or clinical datasets. The collected data are cleaned to address missing observations, duplicate records, inconsistent timestamps, and measurement noise. The data are then aligned to a common temporal scale, such as daily or weekly intervals. Appropriate normalization and feature-extraction techniques are applied to prepare the inputs for mathematical parameter estimation and AI-based forecasting. Training, validation, and test datasets are separated chronologically to prevent information from the future from leaking into the prediction process.

3.4. Formulation of the Fractional-Order SEIR Model

Let the total population be represented by

$$N(t) = S(t) + E(t) + I(t) + R(t),$$

where (S(t)), (E(t)), (I(t)), and (R(t)) denote susceptible, exposed, infectious, and recovered individuals, respectively.

The proposed fractional-order SEIR model is formulated as

$$^{C}D_t^{\alpha} S(t) = -\frac{\beta S(t) I(t)}{N(t)},$$

$$^{C}D_t^{\alpha} E(t) = \frac{\beta S(t) I(t)}{N(t)} - \sigma E(t),$$

$$^{C}D_t^{\alpha} I(t) = \sigma E(t) - \gamma I(t),$$

$$^{C}D_t^{\alpha} R(t) = \gamma I(t),$$

where $0 < \alpha \leq 1$ is the fractional order β is the transmission coefficient, σ is the progression rate γ is the recovery rate, μ is the natural mortality rate, δ is the influenza-associated mortality rate, and Λ is the recruitment rate. The fractional-order model will be calibrated using epidemiological observations and compared with the classical SEIR model obtained when $\alpha = 1$ Validated biosensor observations will be used as supplementary predictive features, not treated as direct estimates of influenza infection without appropriate calibration.

4. RESULTS AND DISCUSSION

The following section describes the proposed evaluation and expected interpretation. Actual numerical results must be obtained from simulations or experimental data before they can be reported as findings. The fractional-order SEIR model will be simulated to investigate the temporal changes in susceptible, exposed, infectious, and recovered populations. Different values of the fractional order α will be examined to determine how memory effects influence epidemic growth, peak infection levels, and recovery patterns.

The simulation results will be compared with those of the classical SEIR model. A better fit to observed influenza data would support the use of fractional-order dynamics for the selected dataset; however, fractional-order models will not be assumed to be superior without empirical evidence. The proposed IoT component will be assessed based on data availability, measurement quality, transmission latency, and the contribution of sensor-derived features to influenza forecasting. Validated viral biomarker measurements, where available, may provide more direct evidence of infection than general physiological measurements. Temperature, heart rate, and oxygen saturation can provide supplementary health information but are not specific to influenza. The discussion will examine whether integrating these observations with laboratory-confirmed cases and epidemiological surveillance improves the timeliness or accuracy of predictions.

4.1. Comparative evaluation of forecasting models

Four model configurations will be evaluated under the same chronological training, validation, and testing procedure.

Model	Purpose
Classical SEIR	Baseline epidemiological prediction
Fractional-order SEIR	Assessment of memory-dependent dynamics
Standalone AI model	Data-driven influenza forecasting
Hybrid SEIR–AI model	Assessment of combined mathematical and AI prediction

Forecasting accuracy will be measured using mean absolute error (MAE) and root mean square error (RMSE):

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|,$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2},$$

Where y_i is the observed number of cases $\hat{y}_i$ is the predicted number of cases, and n is the number of test observations. Lower MAE and RMSE values indicate better predictive accuracy on the evaluated data. The analysis will also consider peak timing error, prediction intervals, and outbreak-detection performance.

4.2. Sensitivity analysis and outbreak prediction

Sensitivity analysis will investigate how changes in transmission, progression, recovery, and fractional-order parameters influence the predicted epidemic trajectory. This analysis can help identify parameters that require more accurate estimation and determine how uncertainty affects outbreak forecasts.

The early-warning component will identify predicted increases in influenza incidence relative to predefined surveillance thresholds. Its performance will be evaluated using sensitivity, specificity, false-alarm rate, and the lead time between an alert and an observed outbreak threshold crossing.

A reliable early-warning system should balance the timely detection of potential outbreaks with the need to avoid excessive false alarms. The proposed framework combines the interpretability of mathematical epidemic modeling with the predictive capabilities of AI and the additional observations available from connected biosensing technologies. The fractional-order SEIR model represents disease progression and memory effects, while the AI component identifies data-driven patterns and potentially corrects systematic model errors. The principal research contribution will be determined by whether the hybrid framework provides measurable improvements over the classical SEIR, fractional-order SEIR, and standalone AI models. The study will also investigate the effects of missing sensor observations, reporting delays, parameter uncertainty, and changes in transmission patterns. The expected outcome is a mathematically grounded framework for influenza forecasting and early-warning support. Its practical usefulness will depend on data quality, rigorous validation, reliable uncertainty estimates, and the ability to generalize predictions to different influenza seasons or populations.

5.CONCLUSION AND FUTURE WORK

This study proposes an integrated framework for modeling and predicting influenza epidemic dynamics using fractional-order SEIR equations, IoT-enabled biosensors, and AI-based forecasting techniques. The fractional-order SEIR model provides a mathematical approach to representing memory-dependent epidemic behavior and the temporal interactions among susceptible, exposed, infectious, and recovered individuals. By incorporating IoT-based data collection, the framework aims to improve the timeliness of disease surveillance and provide relevant information for monitoring changes in influenza

transmission. AI-based forecasting is intended to capture nonlinear patterns and complement the predictions generated by the mathematical model. The proposed hybrid SEIR–AI framework combines the interpretability of compartmental epidemic modeling with the pattern-recognition capabilities of machine learning. Its performance can be evaluated against classical SEIR, fractional-order SEIR, and standalone AI models using MAE, RMSE, peak prediction error, and outbreak-warning accuracy. Sensitivity analysis can further identify the epidemiological parameters that have the greatest influence on predicted infection trends, helping researchers understand the factors associated with changes in disease transmission. Overall, the proposed framework has the potential to support influenza outbreak forecasting, early-warning development, and public health planning. However, its effectiveness must be established through numerical simulations and validation using real-world epidemiological data. Physiological measurements collected through wearable or IoT devices should be treated as supplementary indicators rather than direct confirmation of influenza infection unless validated by appropriate diagnostic methods. With reliable data integration, uncertainty assessment, and external validation, the framework could contribute to more responsive and evidence-based influenza surveillance systems.

Future research will validate the proposed framework using real-world influenza surveillance data. Advanced fractional-order models will be explored to capture complex epidemic dynamics. Deep learning techniques, such as LSTM and Transformer models, will be integrated to improve forecasting accuracy. IoT-enabled biosensors will be investigated for continuous health monitoring and timely data collection.Uncertainty quantification and early-warning mechanisms will be developed to reduce false alarms.Finally, the framework will be tested across different populations and regions to support reliable public health decision-making.

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