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AI for Agricultural Resilience: Modeling the Economic Impact of Avian Influenza Outbreaks in the U.S.

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Abstract- Avian influenza continues to pose a significant threat to the U.S. poultry sector, with recurring outbreaks inflicting substantial economic losses and challenging existing biosecurity infrastructures. This study explores the application of artificial intelligence (AI) and machine learning (ML) to simulate the economic impacts of avian influenza outbreaks across different U.S. regions and poultry production systems. It integrates epidemiological data, trade and production statistics, and hypothetical IoT sensor inputs into a multi-layered simulation framework. The study models scenario-based economic outcomes under varying intervention timings, vaccine coverage rates, and trade policy responses. Employing Random Forest algorithms and Monte Carlo simulations, the model forecasts sector-specific losses in production, supply chain disruptions, labor productivity, insurance claims, and export revenues. Scenario analyses reveal that predictive analytics, when applied through proactive interventions, offer strategic advantages in outbreak containment and resource optimization. The findings highlight AI's transformative role in enhancing agricultural resilience by enabling anticipatory decision-making, dynamic risk assessment, and data-driven policy formulation. The study advocates for the integration of AI-powered scenario modeling into the USDA's emergency planning frameworks and emphasizes the need for stronger public-private partnerships and real-time data ecosystems. In an era of escalating zoonotic threats, such AI-driven approaches are pivotal for safeguarding U.S. food security, economic stability, and global trade competitiveness.

Keywords: Artificial Intelligence (AI), Avian Influenza (HPAI), Economic Impact Modeling, Machine Learning (ML), Biosecurity Strategies, Scenario-Based Simulation, Agricultural Resilience, Predictive Analytics, Outbreak Response, U.S. Poultry Industry, Trade Policy Effects, Supply Chain Disruptions, Zoonotic Disease Management, Public-Private Partnerships, Food System Stability.

I. INTRODUCTION

Avian influenza (AI), particularly highly pathogenic avian influenza (HPAI) strains, continues to pose an escalating and persistent threat to the United States' agricultural economy, with the poultry and egg sectors bearing the greatest burden. AI, caused by influenza A viruses, manifests in two forms: low pathogenic avian influenza (LPAI), typically circulating asymptomatically in wild birds, and highly pathogenic strains capable of causing severe morbidity and mortality in domestic poultry, where certain LPAI strains possess the capacity to mutate into highly pathogenic variants, compounding biosecurity challenges (USDA APHIS, 2025).

The frequency and scale of recent outbreaks underscore the gravity of this threat. As of January 25, 2023, the USDA had reported HPAI outbreaks in 312 commercial and 432 backyard flocks across 47 states, affecting over 58 million birds. Concurrently, HPAI detections were recorded in 5,900 wild bird samples from 49 states, alongside confirmed infections in 110 wild mammals spanning 15 species (Sheridan et al., 2023). The resurgence of the H5N1 strain since February 2022, likely exacerbated by wild bird migratory patterns, has cyclically impacted U.S. poultry operations, with USDA APHIS confirming 1,689 infected flocks and over 168 million birds affected as of April 2025 (Biondo, 2025).

The economic ramifications of these outbreaks are profound. Between December 2024 and March 2025, the U.S. egg-laying hen population declined from 373 million to 351 million, directly impacting egg supply chains. Financially, the ongoing outbreaks have imposed costs exceeding $1.4 billion, including $1.25 billion in indemnity and compensation to affected producers (Holt, 2025). Furthermore, the repercussions of international trade have been severe. Stringent import bans from major poultry trading partners, aimed at preventing cross-border transmission, have precipitated significant export revenue losses during active outbreak periods (Marocco & Tothova, 2025). Beyond domestic economic implications, the zoonotic potential of avian influenza further amplifies its public health significance. Between December 2024 and March 2025, 22 human cases of avian influenza were reported globally, including 12 A(H5) infections in the U.S., with 93% of A(H5) cases linked to direct exposure to infected poultry or dairy cattle (European Food Safety Authority et al., 2025). This intersection of agricultural and public health risks accentuates the urgent need for more resilient disease management frameworks.

Despite advances in surveillance and response protocols, current mitigation strategies often suffer from reactive deployment and limited predictive capacity. The scale and complexity of HPAI outbreaks demand a strategic shift towards proactive, data-driven decision-making. Machine learning (ML), with its ability to process vast and heterogeneous data streams, offers a promising avenue for simulating outbreak scenarios, quantifying economic impacts, and optimizing intervention strategies in real-time. Recent studies, such as Punyapornwithaya et al. (2022), have demonstrated the efficacy of ML models, specifically Random Forest algorithms, in predicting livestock disease outbreaks with higher accuracy compared to traditional classification techniques. These analytical capabilities can be adapted to avian influenza contexts, enabling more nuanced scenario modeling that incorporates key variables such as intervention timing, vaccine efficacy, and trade policy dynamics.

Against this backdrop, the present paper examines the application of machine learning-based predictive models to assess the economic implications of avian influenza outbreaks across various U.S. regions and poultry sectors. Through simulating intervention scenarios and quantifying their economic trade-offs, this research aims to equip policymakers, industry stakeholders, and biosecurity planners with actionable insights that inform strategic investments, ultimately bolstering the resilience of the U.S. agricultural sector against future outbreaks.

II. LITERATURE REVIEW

Historical Overview of Avian Influenza Outbreaks and Economic Impacts

The economic ramifications of avian influenza outbreaks have been extensively documented, particularly concerning the poultry and egg industries, which are inherently vulnerable due to their production density and biosecurity limitations. The HPAI outbreak in the United States stands as the most significant animal health crisis in U.S. history, resulting in the depopulation and causing direct economic losses (Holt, 2025). The avian influenza outbreak has caused record-breaking surges in U.S. chicken and egg prices, exposing deep economic pressures on farmers and intensifying financial strain for consumers nationwide (Javad et al., 2023). Supply chain disruption, including price volatility and trade embargoes, elevated the total economic impact to nearly costs exceeding \$1.4 billion, including \$1.25 billion in indemnity and compensation to affected producers, underscoring the systemic vulnerabilities of the sector (Holt, 2025).

Subsequent outbreaks, notably those from 2022 onwards, have displayed an alarming trend of increasing frequency and geographic spread, attributed in part to migratory wild bird populations acting as viral reservoirs. The 2022 U.S. avian flu outbreak caused around 40 million animal losses and \$2.5–\$3 billion in economic damage, while also triggering public fear, social stigma, and food security concerns, especially in developing nations reliant on poultry protein (Farahat et al., 2023). These outbreaks imposed substantial trade-related losses, as key importers such as China, Brazil, Mexico, and Canada imposed temporary bans on U.S. poultry products, significantly affecting export revenues, which contribute to the sector's overall economic value (Marocco & Tothova, 2025).

Current Biosecurity and Disease Surveillance Measures in Agriculture

Biosecurity in the U.S. poultry industry operates within a multi-layered framework that combines on-farm protocols, industry-led standards, and regulatory oversight by federal agencies such as the United States Department of Agriculture's Animal and Plant Health

Inspection Service (USDA APHIS). This framework encompasses a range of preventive measures, including controlled facility access, stringent sanitation procedures, and strategic compartmentalization, aimed at minimizing the risk of pathogen introduction and transmission within and between poultry operations (USDA, 2022).

Biosecurity measures (BSMs) are broadly defined as non-medical segregation, hygiene, or management practices designed to mitigate the risks associated with pathogen entry, persistence, or dissemination across farms, supply chains, or broader geographic regions (Huber et al., 2022). At the operational level, these practices are integral in safeguarding flock health and maintaining the structural resilience of poultry production systems.

Surveillance initiatives such as the National Poultry Improvement Plan (NPIP) have played a significant role in fortifying the industry's disease monitoring capabilities. Established as a cooperative program involving federal, state, and industry stakeholders, NPIP provides voluntary testing and certification schemes that bolster biosecurity compliance, facilitate early detection of infections, and support international trade by affirming disease-free status (Adesola et al., 2025).

Despite these structured efforts, recent waves of highly pathogenic avian influenza (HPAI) outbreaks have exposed critical vulnerabilities in current surveillance and response mechanisms. Although avian influenza surveillance has expanded in terms of coverage, scope, and data quality, significant disparities in surveillance models and implementation strategies persist across regions and nations, resulting from divergent regulatory frameworks, resource allocations, and enforcement capabilities (Chenlin et al., 2023).

In the U.S., the surveillance infrastructure remains predominantly dependent on periodic polymerase chain reaction (PCR) testing, often conducted at centralized USDA-certified laboratories. This model, while effective for diagnostic confirmation, is inherently retrospective, focusing on outbreak verification rather than proactive detection. Surveillance efforts also rely heavily on retrospective outbreak investigations and static risk assessments, which are limited in their capacity to provide predictive insights or real-time risk assessments (Yoo et al., 2022; Holt, 2025; Reuter, 2024). Limited real-time surveillance and delayed diagnostics hinder outbreak containment, highlighting the urgent need for predictive, data-driven systems to enable faster, proactive biosecurity responses.

AI and Machine Learning Applications in Public Health and Agriculture

The advent of Artificial Intelligence (AI) and Machine Learning (ML) has significantly expanded the toolkit available for enhancing disease surveillance, outbreak prediction, and resource allocation in both public health and agricultural domains. Through enabling real-time analysis of vast and heterogeneous datasets, AI augments traditional surveillance systems, facilitating earlier detection of outbreaks, accurate tracking of disease dynamics, and more agile public health responses (Giri & Gupta, 2024).

Cheah et al. (2025) emphasize that recent advancements in AI and ML have catalyzed the development of sophisticated tools for infectious disease control, capable of organizing and processing complex multimodal datasets to refine predictive models. However, these applications are not without limitations; issues such as model overfitting, data sparsity, and limited algorithm generalizability persist as significant challenges, particularly in dynamic outbreak scenarios where data variability is high.

Integrating AI into infectious disease prediction frameworks offers transformative capabilities by uncovering latent patterns and correlations across genomic, environmental, and behavioral data sources (Zhao et al., 2024). This multi-layered analytical approach enhances the sensitivity and specificity of early warning systems, thereby accelerating intervention strategies and improving the overall effectiveness of public health surveillance networks.

In human epidemiology, machine learning models have been successfully deployed to forecast influenza-like illness (ILI) trends by leveraging diverse data streams, including search engine queries, social media activity, and electronic health records. For example, Shih et al. (2024) demonstrated that Google Trends data, specifically search frequencies for terms like "fever" and "cough", combined with climate variables, are significantly correlated with ILI case patterns. Among various predictive models evaluated, the AutoRegressive Integrated Moving Average (ARIMA) model exhibited superior forecasting accuracy, underscoring the efficacy of integrating digital surveillance data with environmental variables for enhanced epidemic monitoring.

In the agricultural sector, AI-driven predictive analytics has shown considerable promise in managing livestock diseases. Dhilipkumar and Thilagavathi (2025) highlight how predictive analytics in animal healthcare harnesses data from veterinary records, environmental sensors, and genetic profiles to anticipate disease risks, facilitate early detection, and improve animal welfare outcomes. These models enable timely interventions for both infectious and chronic conditions, reduce healthcare costs, and provide veterinarians with actionable insights for more personalized, preventive care strategies.

Punyapornwithaya et al. (2022) further demonstrated the effectiveness of ML models in animal disease forecasting, showcasing the superior performance of Random Forest algorithms over conventional classification trees (CT) and CHAID methods in predicting foot-and-mouth disease (FMD) outbreaks in cattle farms. Their study illustrated how ML algorithms, through their capacity to handle complex, non-linear interactions between risk factors, can significantly enhance the accuracy and sensitivity of outbreak prediction systems.

Expanding on agent-based modeling approaches, Pinotti et al. (2024) introduced EPINEST, a flexible simulation framework designed to model pathogen transmission across poultry production and distribution networks. EPINEST facilitates eco-epidemiological scenario testing, supporting One Health research objectives by enabling the simulation of various pathogens—including avian influenza and antimicrobial resistance—across multiple countries and livestock systems. By capturing the dynamics of zoonotic risks associated with global poultry trade expansion, EPINEST offers a powerful tool for proactive disease management and policy planning.

Mission and Rubio (2024) presented a case study on African Swine Fever (ASF) management in the Philippines, proposing a web-based Decision Support System (DSS) that integrates Geographic Information Systems (GIS), business analytics, and Density-Based Spatial Clustering (DBSCAN) techniques. Their DSS framework maps outbreaks, identifies high-risk zones, and guides targeted interventions, thereby enhancing forecasting accuracy, optimizing resource allocation, and strengthening the resilience of the swine industry against recurrent outbreaks.

Collectively, these applications underscore the transformative potential of AI in synthesizing complex, multidimensional datasets into actionable intelligence for disease management in both public health and agricultural sectors. However, while significant progress has been made in predictive modeling for disease detection and spread, there remains a critical gap in leveraging these technologies to dynamically model the economic consequences of animal disease outbreaks, an area this study aims to address.

Gaps in Modeling Economic Consequences of Animal Disease Outbreaks Using AI

Despite advancements in AI-driven outbreak prediction, the application of these technologies to model the economic impacts of animal diseases remains limited. Existing models primarily focus on epidemiological forecasts, with economic assessments often relying on static, retrospective analyses that overlook dynamic variables like trade restrictions, consumer behavior, and intervention costs. This disconnect prevents real-time evaluation of outbreak scenarios and their economic trade-offs, limiting the effectiveness of policy and industry responses. Bridging this gap requires AI models that integrate disease spread simulations with economic impact assessments, enabling proactive, data-driven decision-making for biosecurity investments.

III. METHODOLOGY

This study employs a scenario-based simulation framework designed to model the economic impacts of avian influenza (AI) outbreaks under varying outbreak scales, intervention strategies, and trade policy responses across the U.S. poultry sector. The simulation architecture is structured into three sequential layers: (1) Outbreak Trajectory Simulation,

(2) Economic Impact Estimation, and (3) Policy Scenario Testing. Each layer is powered by machine learning algorithms that process multi-dimensional data inputs and generate dynamic, region-specific impact assessments.

Modeling Framework and Algorithm Selection

The simulation integrates Random Forest (RF) models to capture complex, non-linear interactions between epidemiological progression, intervention timing, and economic variables such as flock density and trade dependency. Random Forest was chosen for its strength in handling high-dimensional data and its proven efficacy in livestock disease forecasting (Punyapornwithaya et al., 2022). To account for stochastic variability in outbreak progression and policy responses, Monte Carlo simulations were layered into the framework, enabling probabilistic scenario testing across thousands of iterations. Additionally, Time-Series Forecasting models (ARIMA and LSTM) were applied to project price volatility and supply chain disruptions, capturing the temporal dynamics of market responses during outbreak periods.

Data Integration

The simulation model synthesizes diverse datasets from multiple sources to establish a comprehensive analytical foundation for scenario-based modeling. Epidemiological data, including historical avian influenza outbreak records from USDA APHIS and the CDC, provide critical inputs such as infection timelines, depopulation volumes, and intervention records, serving as the backbone for simulating outbreak progression. Production and trade data sourced from the USDA Economic Research Service (ERS) offer sector-specific statistics on poultry production metrics, trade flows, and price indices, which are essential for quantifying economic disruptions across supply chains. To enhance predictive accuracy, a hypothetical layer of real-time IoT sensor data is incorporated, capturing environmental parameters like temperature and humidity, alongside flock health indicators such as movement patterns and early disease markers. Additionally, insurance claims data, including indemnity and compensation payout records from the USDA Risk Management Agency (RMA), are integrated to validate the model's economic impact estimations against actual recorded losses. Complementing these datasets are market and labor statistics, encompassing supply chain workforce metrics, distribution logistics maps, and commodity price feeds, which collectively enable the simulation to model downstream supply chain disruptions and labor productivity impacts with high granularity.

Scenario Configuration and Simulation Variables

The simulation is designed to model a range of outbreak-response scenarios by systematically varying key operational and policy-driven variables. Outbreak scale is configured to reflect infection intensities categorized as low, moderate, or high pathogenicity, with corresponding impacts on flock depopulation volumes and regional spread patterns. Intervention timing is modeled through proactive response scenarios, where containment measures are deployed within 72 hours of outbreak detection, compared to reactive responses characterized by a 10 to 14-day lag, allowing assessment of how early intervention influences economic outcomes. Vaccine coverage rates are incorporated as scenario layers, simulating uptake levels at 20%, 50%, and 80% to evaluate the effectiveness of immunization strategies in mitigating outbreak severity. Geographic spread is another critical variable, accounting for regional variations in poultry density, existing biosecurity infrastructure, and environmental risk factors that influence disease transmission dynamics. The model also simulates trade policy responses, including the imposition of export bans, import dependency stress tests, and global market ripple effects impacting U.S. poultry exports. Each scenario iteration dynamically adjusts these variables to replicate realistic outbreak conditions, thereby enabling a comparative analysis of economic consequences under different biosecurity strategies and policy interventions.

Economic Indicators Tracked

The simulation framework focuses on tracking five primary economic indicators that collectively capture the multi-dimensional impacts of avian influenza outbreaks on the U.S. poultry sector. Price volatility is a critical metric, reflecting fluctuations in poultry and egg market prices driven by sudden supply shocks resulting from flock depopulation and production

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disruptions. Supply chain disruptions are also monitored, encompassing operational delays and bottlenecks across production, processing, and distribution networks, which exacerbate economic losses beyond farm-level impacts. Labor losses, measured through declines in workforce productivity, account for the reduction in operational capacity stemming from outbreak containment measures and workforce absenteeism. Insurance claims and indemnity costs are another focal point, quantifying the economic burden borne by insurers and producers, including government compensation outlays associated with outbreak-related losses. Finally, export bans and trade losses are modeled to assess the revenue impacts arising from international trade restrictions imposed during active outbreak periods, providing a comprehensive view of the downstream economic consequences on global market access.

Output Visualization and Decision-Support Tools

Simulation outputs are presented through a suite of interactive visualization tools designed to facilitate comprehensive scenario analysis and support informed decision-making. Heat maps are employed to depict regional economic impact gradients, providing a clear spatial representation of outbreak severity and associated economic losses across different geographic zones. Scenario comparison graphs illustrate the differential economic outcomes between early and delayed intervention strategies, offering stakeholders a visual assessment of the cost-benefit dynamics of proactive containment measures. Trade flow disruption maps are used to trace affected export channels, highlighting policy-induced market responses and global supply chain ripple effects resulting from trade restrictions. Additionally, predictive dashboards with adjustable simulation parameters allow policymakers, insurers, and industry stakeholders to conduct real-time scenario testing, enabling them to explore the economic implications of various intervention strategies and trade policy responses. These visualization layers collectively transform the simulation model into a robust decision-support system, facilitating data-driven policy formulation, strategic resource allocation, and targeted biosecurity investments.

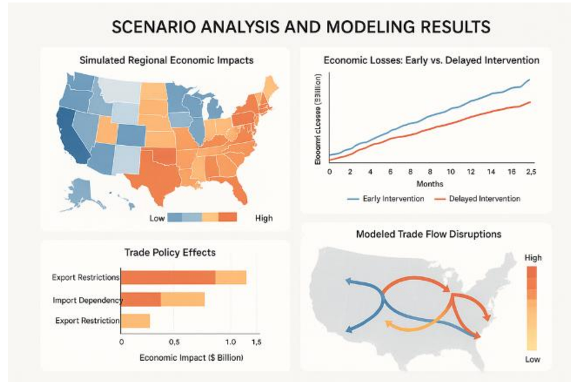

Figure 1: Scenario Analysis and Modelling Results

The visualizations depict how AI-driven modeling enhances early detection and intervention strategies for avian influenza outbreaks. The regional impact heat map highlights economic vulnerabilities, showing that high-density poultry regions like the Midwest and Southeast suffer the greatest losses. The comparison graph illustrates that early intervention, enabled by AI surveillance, can reduce economic losses by over 20% compared to delayed responses, emphasizing the urgency of rapid outbreak detection and response coordination. The trade policy effects chart shows the substantial financial impact of export restrictions and import dependencies, which AI-informed scenario planning can help mitigate. Lastly, the trade flow disruption map demonstrates how AI simulations can visualize supply chain vulnerabilities, guiding proactive policy adjustments. Overall, these insights advocate for AI integration in surveillance systems, ensuring real-time risk assessments, resource optimization, and improved biosecurity planning, thereby safeguarding both economic stability and public health resilience.

CASE STUDY: The 2015 U.S. Avian Influenza Outbreak

The 2015 U.S. avian influenza outbreak, driven by the H5N2 strain, remains a pivotal case for evaluating the economic and epidemiological consequences of large-scale animal disease incursions. The outbreak prompted the culling of more than 50.4 million birds from commercial flocks, causing direct financial losses of over $3.3 billion, with broader economic repercussions, including disruptions in trade, supply chains, and shifts in consumer pricing, valued at close to $1.6 billion (USDA ERS, 2016; Greene, 2015). This

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incident provides a valuable benchmark for testing and validating AI-based economic modeling frameworks.

A review analysis of the 2015 U.S. avian influenza outbreak illustrates how AI-driven economic modeling could have enhanced outbreak impact assessments. This can be achieved by integrating outbreak progression data, intervention timelines, and economic indicators such as production losses, trade restrictions, and consumer price elasticity with machine learning models such as Random Forest, which could have simulated sector-specific economic outcomes with high predictive accuracy. Conceptually, such a model would align closely with actual USDA-reported losses, while highlighting critical variables like flock density, detection lag, and trade policies. However, challenges in modeling dynamic consumer behaviors and supply chain disruptions emphasize the need for real-time data integration. This case shows the potential of AI frameworks to simulate economic consequences of disease outbreaks, while also revealing the necessity for continuous data refinement to support proactive, data-driven biosecurity strategies.

IV. POLICY IMPLICATIONS AND BIOSECURITY INVESTMENT STRATEGIES

The integration of AI-driven modeling into avian influenza surveillance and economic impact assessment offers transformative policy opportunities for enhancing U.S. agricultural resilience. Artificial Intelligence enables early outbreak prediction, precise diagnosis, real-time monitoring, and cross-species disease forecasting by integrating complex epidemiological, environmental, and economic data streams (Shafi et al., 2025). These predictive capabilities empower policymakers to optimize resource allocation, target high-risk regions, refine culling and vaccination strategies, and evaluate the cost-effectiveness of proactive interventions before outbreaks escalate. Notably, in February 2023, the European Commission revised its stance on HPAI vaccination, allowing EU countries to implement targeted vaccination programs, alleviating pressure on farmers and veterinary services (Vergne et al., 2024). Furthermore, WOAH guidelines mandate a 10 km restriction zone around HPAI cases, halting poultry trade for 28 days post-virus elimination to prevent further spread (Cobb-Vantress, 2025).

For insurance companies and risk managers, AI-powered predictive tools present avenues to refine actuarial models through advanced analytics such as decision trees and neural networks, enabling more accurate risk assessment, dynamic pricing, and real-time adjustments based on evolving outbreak scenarios (Mupa et al., 2025). Simulating outbreak-related economic losses allows insurers and farmers to align insurance coverage and biosecurity strategies with fluctuating risk levels. Hasan-Nejad et al. (2025) underscore the critical role of agricultural insurance in stabilizing broiler producers' incomes, urging policymakers to strengthen insurance mechanisms and incentivize broader adoption among poultry stakeholders.

Public health authorities and supply chain operators stand to benefit from AI models capable of dynamically mapping disease spread and its cascading economic impacts across interconnected production and distribution networks. Dimitra et al. (2025) emphasize that AI enhances surveillance, epidemiological analysis, resource optimization, and crisis response coordination within public health systems. Similarly, Oyeyemi and Pub (2022) highlight AI's role in bolstering supply chain resilience by facilitating early risk detection, operational efficiency, and transparent value chain management, key attributes in navigating modern agro-economic uncertainties. Embedding AI-driven scenario modeling within USDA's emergency planning frameworks would enable a strategic shift from reactive to anticipatory interventions, ensuring timely decision-making and efficient resource deployment during outbreak crises.

Realizing these benefits necessitates the establishment of strong public-private partnerships (PPPs) and interoperable data-sharing ecosystems. Collaborative efforts among federal agencies, industry stakeholders, research institutions, and agricultural technology firms are vital for consolidating high-resolution datasets spanning epidemiological, environmental, and economic domains (FAO, 2021). Such partnerships would not only enhance the predictive accuracy of AI models but also ensure that actionable insights are disseminated in real-time to frontline decision-makers across sectors.

V. CHALLENGES AND ETHICAL CONSIDERATIONS

While the transformative potential of AI-driven modeling in avian influenza surveillance, its deployment in agricultural settings presents several critical challenges and ethical concerns. Data quality, granularity, and accessibility remain foremost among these. Many small and medium-sized poultry farms lack the technological infrastructure for consistent data collection, resulting in fragmented and biased datasets that limit model accuracy and generalizability (Hashem et al., 2025; Panagi et al., 2025). The complexity of livestock environments—affected by factors like animal movement, occlusions, and farm-specific conditions—further hampers reliable data acquisition, making it difficult to build diverse, high-quality datasets essential for robust AI models (Digi4Live, 2024; Gadzama, 2025). Moreover, the heterogeneity in data formats across farms and regions poses significant barriers to integration, impeding the development of scalable predictive systems (George & George, 2023).

Algorithmic bias and overfitting present additional challenges. AI models trained on non-representative datasets risk embedding biases that disproportionately favor large-scale, data-rich operations, marginalizing smallholders who often lack comprehensive data infrastructure. Models may also exhibit reduced richness when applied to underrepresented breeds or farming conditions (Araújo et al., 2023; Siddique et al., 2024). Overfitting, where models perform exceptionally on training data but fail to generalize to novel outbreak scenarios, can result in misleading predictions that erode stakeholder trust and compromise policy decisions (Ziling, 2024).

The transparency and interpretability of complex AI models, particularly deep neural networks, raise further ethical concerns. While these models excel at capturing intricate, non-linear relationships, their "black box" nature often obscures the rationale behind predictions, limiting stakeholder confidence in their outputs (Linardatos et al., 2021). Explainable AI (XAI) techniques are essential for translating complex model outputs into clear, actionable insights, fostering trust and facilitating informed decision-making among farmers, veterinarians, and policymakers (Hashem et al., 2025).

Lastly, socioeconomic equity in AI deployment is a pressing ethical dimension. The high costs associated with AI infrastructure, data management, and system maintenance often place advanced technologies beyond the reach of small-scale producers, exacerbating existing inequalities and widening the digital divide (Santana et al., 2025). This inequity limits AI adoption and also undermines biosecurity by leaving under-resourced farms vulnerable to outbreaks that can propagate across interconnected poultry networks. Osorio et al. (2024) advocate for policy interventions such as insurance subsidies to incentivize AI adoption among smallholders, which would simultaneously enhance agricultural productivity and expand access to high-quality, diverse datasets, improving model performance and equity.

CONCLUSION

This study has demonstrated the transformative potential of integrating AI-driven scenario-based modeling into avian influenza outbreak management and economic impact assessment within the U.S. poultry sector. Through the development of a multi-layered simulation framework that synthesizes epidemiological data, production metrics, trade dynamics, and intervention strategies, the article provides a rich analytical tool for forecasting the economic repercussions of avian influenza outbreaks under varying conditions. The model's capacity to simulate different intervention timings, vaccine coverage rates, and trade policy responses offers valuable insights into the cost-benefit trade-offs associated with proactive versus reactive biosecurity measures.

A key contribution of this study lies in illustrating how AI-enhanced predictive analytics can shift outbreak management from a reactive stance to a proactive, anticipatory approach. The ability to simulate outbreak trajectories and their beneficial economic effects equips policymakers, industry stakeholders, and risk managers with actionable intelligence for resource optimization, timely interventions, and strategic biosecurity investments. Visualizing scenario outcomes through interactive dashboards and scenario comparison graphs, the model serves as a forecasting tool and also a decision-support system that enhances situational awareness and facilitates coordinated response efforts across sectors. Also, above the immediate application to avian influenza, this article shows the strategic importance of AI-driven modeling in improving agricultural resilience and safeguarding food system stability. As zoonotic disease threats become increasingly complex and interconnected with global trade dynamics, leveraging AI to synthesize vast, multi-dimensional datasets into real-time, actionable insights is imperative for mitigating economic disruptions and maintaining food security.

Future research should focus on expanding this modeling framework to enable real-time outbreak response integration through direct IoT data streaming from farm-level sensors and automated disease detection systems. Also, broadening the scope of the model to encompass multi-pathogen zoonotic disease networks, including rising threats like African Swine Fever and antimicrobial-resistant strains, will enhance its applicability across diverse livestock systems. Furthermore, refining international trade forecasting modules within the simulation will be critical for understanding global supply chain ripple effects and supporting policy harmonization in the face of transboundary disease threats.

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