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State-Level Influenza Hospitalization Burden in the United States, 2022–2023

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CONTRIBUTORS

All of the authors were involved in the study conceptualization. A. Couture, A. D. Iuliano, R. Threlkel, M. Gilmer, M. Biggerstaff, and C. Reed analyzed the primary and input data. A. Couture and H. H. Chang coded the model and A. Couture was responsible for running model analyses. A. Couture, A. D. Iuliano, R. Threlkel, M. Gilmer, A. O'Halloran, and D. Ujamaa validated the data used in the analysis. A. Couture, A. D. Iuliano, M. Biggerstaff, and C. Reed led the initial drafting of the article. All of the authors contributed ideas for analysis and to editing of the article.

CONFLICTS OF INTEREST

The authors declare that they have no competing interests.

HUMAN PARTICIPANT PROTECTION

This activity was reviewed by the Centers for Disease Control and Prevention and determined to be consistent with non-human participant research activity. Informed consent was waived as the data were de-identified and aggregated.

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Abstract

Objectives.—To develop a method leveraging hospital-based surveillance to estimate influenza-related hospitalizations by state, age, and month as a means of enhancing current US influenza burden estimation efforts.

Methods.—Using data from the Influenza Hospitalization Surveillance Network (FluSurv-NET), we extrapolated monthly FluSurv-NET hospitalization rates after adjusting for testing practices and diagnostic test sensitivities to non-FluSurv-NET states. We used a Poisson zero-inflated model with an overdispersion parameter within the Bayesian hierarchical framework and accounted for uncertainty and variability between states and across time. Model validation included checking the sensitivity of results to input data, as well as model convergence diagnostics and comparing the results with independent data sources.

Results.—We estimated 379 300 (90% credible interval [CrI] = 305 400, 479 300) influenza-related hospitalizations in the United States for the 2022–2023 season. Median cumulative state rates ranged widely from 23.2 to 249.0 per 100 000 people.

Conclusions.—Our estimates were comparable to national burden estimates incorporating other approaches while accounting for variations in the timing and geography of disease activity and changes in detection and reporting. Our results provide a complementary framework to calculate estimates at finer geographic scales.

The Centers for Disease Control and Prevention (CDC) has estimated the national influenza disease burden annually in the United States since the 2010–2011 season. Disease burden models help estimate the full impact of the disease, unlike other disease-related indicators that are often affected by care seeking, testing practices, and reporting.¹ Disease burden estimates provide a more complete picture of the true impact of a disease on public health and society, which is often unrecognized through case counting. By understanding the influenza disease burden, public health officials can better assess disease severity and target prevention and control measures to reduce morbidity and mortality. Currently, cumulative deaths, hospitalizations, medically attended illnesses, and symptomatic cases are estimated at the national level each week during and at the end of each season by age group. During the 2022–2023 season, the CDC estimated that 298 700 to 678 200 influenza-related hospitalizations occurred.²

Although the CDC has a long-established history of estimating the influenza disease burden at the national level, routine and robust methods to estimate state-level influenza-related hospitalization burdens have been lacking. During the 2009 influenza pandemic, the CDC began reporting timely national disease burden estimates that adjusted for underdetection, and methods have continued developing since; however, there is not yet state-level reporting.^{3,4}

Currently, some state health departments report influenza hospitalizations on their Web sites. They often report data on hospitalizations from the Influenza Hospitalization Surveillance Network (FluSurv-NET) or the National Healthcare Safety Network (NHSN), which present unadjusted reported numbers.^{5,6} Although these systems and numbers are extremely useful and important, crude or unadjusted reports of surveillance data underestimate the true burden of influenza hospitalizations as a result of multiple underdetection factors.^{3,7}

There have been ad hoc efforts to estimate influenza burdens at state levels. One study estimated influenza-related hospitalizations in Utah with adjustment for testing practices, and another study in Washington used the state-wide hospitalization system and modeled influenza hospitalization incidence; however, neither investigation accounted for testing practices or diagnostic assay sensitivities.^{8,9} Although these studies provide useful information on the burden of disease in specific states, they do not serve as national models accounting for uncertainty and allowing for stratification by state, age, and month. Drawing inspiration from a previous study that estimated the global influenza burden by leveraging country-level reported data, we recognize the inherent variability in the influenza burden among states, as with the variation between countries.¹⁰

Accurate state-level estimation of influenza-related hospitalizations is important for public health planning, assessments of the impact of preventive measures, and resource allocation. We adapted methods from a project designed to estimate COVID-19 state-level hospitalizations during the pandemic that leveraged available surveillance data and employed a Bayesian hierarchical model.¹¹ We aimed to provide state-level influenza-related hospitalization estimates modeled with an understanding of spatial and temporal patterns to complement current national hospitalization burden estimates. Our objective was to calculate monthly state-level influenza-related hospitalization rates by multiple age groups. We applied this new method to the 2022–2023 influenza season.

METHODS

We used hospitalization case count data from the CDC's FluSurv-NET collected during the 2022–2023 season. The network conducts population-based surveillance of hospitalized patients with a positive laboratory influenza test during a hospitalization or within 14 days before a hospitalization. The network includes hospitals in approximately 77 selected counties across 14 participating sites in 13 states: California, Colorado, Connecticut, Georgia, Maryland, Michigan, Minnesota, New Mexico, New York (2 sites; combined for this analysis), Ohio, Oregon, Tennessee, and Utah.

Catchment areas are defined according to patient residence within the selected counties; most data are received from hospitals inside the catchment area. Residents in each catchment area within a state are combined to create the population denominator for calculation of hospitalization rates. The network covers a total catchment population of more than 27 million people, representing about 9% of the US population. The network has been described in detail elsewhere.¹² For our model, the data were aggregated by state, month of hospitalization, and 7 age groups: 0 to 4, 5 to 17, 18 to 49, 50 to 64, 65 to 74, 75 to 84, and 85 years or older. Data are collected from October 1 through April 30 for each influenza

season. Therefore, our hospitalization estimates span the period October 2022 through April 2023.

Because not all hospitalized patients undergo influenza testing, we corrected influenza hospitalization rates for underdetection by applying weights based on influenza testing practices and diagnostic test sensitivity using methods described previously.⁴ Influenza testing practices were defined as the probability that a person who was hospitalized with a respiratory infection was tested for influenza in participating FluSurv-NET hospitals.⁴ Data on testing practices during the 2022–2023 season were unavailable at the time of this study. For the most conservative adjustments, we used the highest observed testing probabilities over 10 influenza seasons (2010–2011 through 2019–2020) by state, month, and age. Ohio was the only FluSurv-NET site without site-specific testing probabilities, so data from all sites were combined by age and month for each season and the highest observed testing probability across seasons was used for the adjustment. Testing probabilities for different states, months, and age groups ranged from 0.1 to 1.0.

In addition, rates were adjusted for diagnostic test sensitivity. The assay sensitivity data were obtained from the literature and ranged from 0.76 to 0.91.⁴ We calculated adjusted hospitalization rates using FluSurv-NET catchment populations for each state. Seven distinct models were employed for each age group:

$$Adjusted\ Flu\ Count_{sm} = \frac{Raw\ Flu\ Count_{sm}}{\left\{ \frac{Prob.\ of\ Being\ Tested_{sm}}{Testing\ Sensitivity} \right\}} \quad (1)$$

where $s=1, \dots, S$ for each FluSurv-NET state and $m=1, \dots, M$ for each month.

Covariates

To extend influenza hospitalization rate estimates beyond FluSurv-NET states to those not included in the network, we incorporated covariates based on state-, month-, and age-specific demographic and epidemiological data. We used various data from multiple sources to address differences between states included and not included in FluSurv-NET (Table A, available as a supplement to the online version of this article at <http://www.ajph.org>). Including subpopulation-specific covariates allowed us to estimate hospitalizations by age group, month, and state. Covariates were both time-varying and fixed state-level factors.

Time-varying covariates included the percentage of positive influenza tests from commercial and public health laboratories (obtained from the National Respiratory and Enteric Virus Surveillance System), the percentage of all-cause deaths attributed to influenza based on National Center for Health Statistics data from the National Vital Statistics System, the percentage of the population vaccinated against influenza (FluVax), the percentage of outpatient visits to health care providers for an influenza-like illness (from the US Outpatient Influenza-like Illness Surveillance Network), and hospital capacity indicators such as the percentage of influenza patients among all inpatients and the percentage

of intensive care unit beds occupied among all available intensive care unit beds (from NHSN).^{6,13–16}

To account for the lag between symptom onset and hospitalization, we included the percentage of influenza tests that were positive with a 1-week lag. Likewise, a 1-week lead was added to the percentage of influenza deaths among all deaths to address the gap between hospitalizations and death. In the case of hospital capacity data, if hospitals reported less than 80% of days in a given month, they were excluded from state calculated percentages. Regarding time-invariant covariates, we used the percentages of non-White and Hispanic populations from 2021, state rural-to-urban proportions from 2020, Social Vulnerability Index variables from 2020, and the prevalence of certain comorbid conditions from 2021 (obtained from the Behavioral Risk Factor Surveillance System).^{17–20} For age groups younger than 18 years, only asthma and obesity were included as chronic condition or disease covariates because of insufficient evidence that the prevalence of other chronic conditions or diseases affected those groups.

Outliers for each time-varying covariate, such as extreme values, were identified and mitigated through the Winsorization process.²¹ We used adjusted influenza hospitalization rates as the outcome variable to guide the selection of covariates, and this procedure was carried out independently for each age group. The method employed for covariate selection was the spike and slab approach within the Bayesian model.²² This robust method aided in identifying and incorporating the most predictive covariates into the final model for each age group while accounting for model selection uncertainties.

Bayesian Hierarchical Model

Building on previous work, we implemented a Poisson zero-inflated model with an overdispersion parameter within a Bayesian hierarchical framework. Let A_{sm} denote the estimated adjusted influenza hospitalization counts from the FluSurv-NET states during the influenza season starting in October 2022; states are represented as $s=1, \dots, S$, with $S=13$ states in FluSurv-NET, and months are represented as $m=1, \dots, M$, with $M=7$ for each month included in the model. A Poisson probability distribution was assumed for the observed hospitalization count. These estimated adjusted influenza hospitalization counts, along with the FluSurv-NET catchment populations and selected covariates, were used in the following Bayesian hierarchical model:

$$\text{Level 1: } A_{sm} \sim \text{Pois}(\theta_{sm} * \text{Population}_s / 100,000)$$

$$\begin{aligned} \theta_{sm} &= \phi_{sm} * Z_{sm} \\ Z_{sm} &\sim \text{Bern}(\rho) \end{aligned}$$

(2)

where $A_{sm} = \text{Adjusted FluSurv-NET Count}_{sm}$ (the adjusted hospitalization count from FluSurv-NET), Population_s is the catchment population for state s , θ_{sm} and ϕ_{sm} are the unobserved true hospitalization rates, and z_{sm} is an indicator for whether the rate is zero.

$$\begin{aligned}
 \text{Level 2: } \boldsymbol{\varphi}_{sm} &\sim \log\text{Normal}(\boldsymbol{\mu} + \sum_{j=1}^k \gamma_j X_{smj} + \boldsymbol{\delta}_{sm} \boldsymbol{\sigma}^2) \\
 \boldsymbol{\delta}_{sm} &\sim N(0, \boldsymbol{\tau})
 \end{aligned}
 \tag{3}$$

where X is the covariate matrix and δ is the overdispersion parameter.

$$\begin{aligned}
 \text{Level 3: } \gamma_k &\sim N(0, 1000000^{(1-g_k)} * 0.001) \\
 g_k &\sim \text{Bern}(0.25) \\
 \text{Priors: } \boldsymbol{\mu} &\sim N(0, 10^{-6}) \\
 \boldsymbol{\sigma}^2 &\sim \text{Unif}(0, 1000) \\
 \boldsymbol{\rho} &\sim \text{Unif}(0, 1) \\
 \boldsymbol{\tau} &\sim \text{Gamma}(0.001, 0.001)
 \end{aligned}
 \tag{4}$$

where $k=1, \dots, K$ and K is the number of selected covariates.

We carried out inference calculations using Markov chain Monte Carlo simulations with 110 000 iterations, 10 000 burn-ins, and thinning of 2 with the “rjags” package in R software version 4.1.2 (R Foundation for Statistical Computing, Vienna, Austria), which interfaces between R and JAGS software version 4.3.0 (<https://sourceforge.net/projects/mcmc-jags>). The model outputted the posterior distribution of influenza-related hospitalizations for each state and month. We calculated medians and 90% credible intervals (CrIs) for hospitalization counts, rounded to hundreds because of Monte Carlo errors, and used 2021 state and age populations to calculate hospitalization rates. Posterior samples were summed to calculate all-age, age by month, age by state, and state by month hospitalizations and rates.

The medians of sums did not equal the sums of medians, which led to slightly different total hospitalizations depending on which grouping was used to sum. Total hospitalizations were calculated from all-age medians, age by month medians, and age by state total medians. We took a Bayesian approach to incorporate multiple levels of variability and have a flexible framework for a hierarchical approach. We chose vague priors for our model’s iteration (as defined in the model); as state-level data become more available, however, priors can be adjusted to be more informed. Priors were varied slightly to check the robustness of the results.

Sensitivity and Comparisons

We conducted multiple sensitivity and comparison analyses to assess the performance of the model. First, we compared the model’s aggregate national rates by age group to the CDC burden estimates from the 2022–2023 season.² Second, to validate the model, we removed each FluSurv-NET state, one at a time, and compared how the model estimated hospitalizations for the removed state with the FluSurv-NET adjusted hospitalization rate.

Third, we compared the model’s state estimates with NHSN data.⁶ Developed and managed by the CDC, NHSN provides a standardized platform for health care facilities to monitor health care–associated infections and includes state-level hospitalization data for influenza

hospitalizations by week. According to [Healthdata.gov](https://healthdata.gov), NHSN data have reliable counts of new influenza hospitalizations starting on February 2, 2022, as a result of mandatory influenza reporting. However, the NHSN data are derived from reports at the facility level and do not account for nonresponse, nontesting, test sensitivity, or missing data. Finally, we compared the model's state estimates with hospitalizations reported by state health departments. We compiled data publicly posted to each state's health department Web site that provided influenza-related hospitalizations at the end of the 2022–2023 season. Sources and notes on each source are detailed in Table B (available as a supplement to the online version of this article at <http://www.ajph.org>).

RESULTS

From October 2022 through April 2023, our model estimated 379 300 (90% CrI = 305 400, 479 300) influenza-related hospitalizations in the United States, with a cumulative hospitalization rate of 114.5 (90% CrI = 92.2, 144.7) per 100 000 people. Rates varied by age, state, and month. The highest estimated rate of cumulative hospitalizations for the 2022–2023 season was in New York, with a rate of 249.0 (90% CrI = 205.1, 303.7) per 100 000 people from an estimated count of 49 400 (90% CrI = 40 700, 60 200). The lowest estimated cumulative hospitalization rate was in Alaska, with a rate of 23.2 (90% CrI = 13.8, 38.8) per 100 000 people from an estimated count of 170 (90% CrI = 100, 280). Figure 1 and Figure A (available as a supplement to the online version of this article at <http://www.ajph.org>) show the cumulative hospitalization rate for each state. In Figure 1, cumulative hospitalization counts by state are presented to show the difference in burden of counts versus rates. FluSurv-NET states were well distributed throughout all state estimates.

Hospitalization rates varied by age group. The highest cumulative rate was observed among those aged 85 years or older, with a rate of 625.2 (90% CrI = 507.4, 768.0) per 100 000 people. The lowest cumulative rate was observed among those aged 18 to 49 years, with a rate of 47.7 (90% CrI = 39.5, 55.0) per 100 000 people (Table 1). Hospitalization rates for all age groups peaked in December 2022 except for those aged 5 to 17 years; the rate for this group peaked in November 2022 (Figure B, available as a supplement to the online version of this article at <http://www.ajph.org>). Across all ages, the largest peak occurred in December 2022 (51.1 per 100 000), followed by November 2022 (41.7 per 100 000), and the lowest occurred in April 2023 (2.2 per 100 000).

Monthly state-level hospitalization rates varied widely, with different timings and magnitudes of peaks. For example, some states (e.g., Arkansas and Michigan) were estimated to have discrete peaks, whereas other states had multiple months with higher hospitalizations (e.g., Connecticut and Illinois). Figure C (available as a supplement to the online version of this article at <http://www.ajph.org>) shows each state's curve over time, highlighting the variability in the influenza-related hospitalization burden between states and within states by month. Varying model priors had no impact on the results.

According to the comparison analysis, this state-level model produced similar estimates to published national burden estimates by age group (Figure 2). The median hospitalization rate produced by the model falls inside the 95% uncertainty intervals of published burden

estimates for all age groups, and the mean hospitalization rate of the published burden falls within the model's 90% credible intervals for all ages. For the sensitivity analysis in which FluSurv-NET states were dropped one at a time, model estimates were mostly consistent whether inputted to build the model or extrapolated (i.e., dropped from the model). Most of the FluSurv-NET states' extrapolated estimates had overlapping credible intervals (Figure 3). When they did not overlap, extrapolated estimates were lower except for Ohio's and Oregon's peak months, which were higher when extrapolated.

When making comparisons at the state level, we found a wide range of similarities with and discrepancies from our model estimates, NHSN, unadjusted FluSurv-NET rates, and hospitalizations reported by state health departments. Figure C shows states where all sources agreed, but we also observed instances in which state-reported rates were higher than our model estimates and NHSN. In general, our model estimates caught overall timing trends and were slightly higher than other sources of reported hospitalizations at the state level, most likely because of our adjustments for testing probability and diagnostic sensitivity.

DISCUSSION

Overall, we estimated that 379 300 cumulative influenza-related hospitalizations occurred in the United States from October 2022 through April 2023. Our model estimated national influenza-related hospitalizations by age group similar to CDC published burden estimates. Our model showed that there was wide variability between states and within states between months with respect to influenza-related hospitalizations during the 2022–2023 season. We found that most states peaked in November and December 2022, following trends observed in influenza surveillance indicators (Figure C).

From our sensitivity analysis, we found that our model was able to reasonably estimate data for states when they were dropped as an input. When there was discordance between estimates, the extrapolated estimates were often more conservative. When comparing our estimates with available outside sources, such as NHSN and figures reported by state health departments, we found that our model was well validated in trends but that there were important differences in magnitude and peak timing. For example, if a state started to peak in November according to our model, it was often not detected in the other sources. This could have been due to early peaking being missed by incorporating the probability of being tested. However, our credible intervals often covered other sources.

Our study introduces a novel approach leveraging state-level information and providing granularity across states, months, and age groups. The absence of such state-level estimates has been a gap in the CDC's efforts to understand the burden of influenza across the country and has limited the understanding of the spatial and temporal dynamics of influenza-related hospitalizations. Our findings underscore the critical role of state-level data in capturing the variable impact of influenza, revealing spatial and temporal patterns that might otherwise be obscured by national-level analyses. Our method aimed to create estimates that account for variation in the timing and geography of disease activity and changes in detection and

reporting to produce monthly state-level estimates at the end of the influenza season. This approach provides a framework for monitoring disease burden using surveillance data.

We found that the unadjusted estimates from FluSurv-NET and NHSN aligned well with our results. The difference between our results and NHSN was expected because, unlike our model, the data from the NHSN system did not account for testing practices and sensitivity. This difference limited comparability between our estimates and reporting sources and the ability to know whether our model estimated the true level of the influenza-related hospitalization burden. There is no available true gold standard with which to compare hospitalization burden estimates because sources do not account for reasons hospitalizations may be underascertained, including the propensity to test individuals for influenza and test performance. Therefore, there is still potential for future work in this framework, including refining the model to account for evolving influenza strains or integrating real-time data to improve the timeliness and accuracy of estimates.

The method's adaptability, drawn from experiences during the COVID-19 pandemic, speaks to its potential for creating a framework applicable beyond the current study.¹¹ Our model is also advantageous in the context of influenza, wherein dynamics exhibit considerable temporal and spatial variability. The Bayesian framework accommodates uncertainty inherent in disease burden estimation, in which factors influencing hospitalization rates may exhibit considerable fluctuations. The ability to quantify uncertainties is crucial when interpreting and using results in public health decision making. Furthermore, the model allows for the incorporation of additional covariates. As new information becomes available or as the landscape of influenza evolves (e.g., availability of large-scale wastewater data for the influenza virus), the model can be updated to reflect these changes so that the estimates remain current and relevant. This adaptability is pertinent in the context of emerging infectious diseases, in which the ability to integrate evolving information enhances the utility and longevity of the methodology.

Limitations

Our study has several limitations. First, our approach relies on the assumption that FluSurv-NET sites are representative of the entire state. The composition of FluSurv-NET sites varies across states; in some states, they encompass most counties, whereas in others they include only a small number of counties. Consequently, our model may involve overestimation or underestimation for FluSurv-NET states depending on the extent to which the catchment area aligns with the influenza activity in the entire state. Despite our efforts to accommodate state-level variability and uncertainty within the model, our ability to accurately capture the full state's reality is constrained by the representativeness of a FluSurv-NET site relative to the entire state and might be biased with respect to the variability of testing practices across the state.

Second, we assume that FluSurv-NET states encompass sufficient diversity to extrapolate data to all states. Although the states within FluSurv-NET exhibit variability across multiple dimensions, we cannot guarantee that they encompass the full spectrum of variations in influenza-related hospitalizations, including adequate rural representation or use of respiratory illness mitigation strategies.

Third, our reliance on covariates to inform extrapolation is constrained by the quality, completeness, and availability of data. Essential information pertaining to influenza-related hospitalization rates, such as underlying risk factors in the population, could be missing. However, our model does incorporate time-varying covariates that describe the seasonal impact in each state, including metrics such as vaccination rates.

Fourth, some states have wide credible intervals, increasing the margin of error in determining actual hospitalization figures and inferring medians. In addition, we did not adjust for test specificity because specificities in hospital settings were high, ranging from 96% to 100% regardless of age group.^{23,24} Although adjustment for false-positive test results might decrease our estimates, the impact on the overall rates would be minimal. Finally, our approach involved distinct models for each age group, restricting our ability to interpret hospitalization estimates by month and state, potentially underestimating variability, and failing to capture correlations between age groups.

Conclusion

Our independent approach aligns with the results of published burden methods. Our method helps provide a better understanding of the actual burden of influenza in the United States because observed hospitalization data are likely to underrepresent the true burden of influenza owing to testing practices and test sensitivity. Furthermore, developing a method to estimate postseason, state-level burdens enhances our understanding of the impact of influenza by state and time. Our method offers a way to estimate state-level influenza hospitalization burdens for all states using routinely collected surveillance and demographic data. State-level estimates can also be used for further public health awareness (e.g., vaccine-avoided burden). Our method, initially used to estimate the global influenza burden and then the US COVID-19 burden, may be useful as well for other levels of the disease burden pyramid or other diseases. Our estimates can help in better informing the differential burden of influenza by state over time and better understanding the potential impact of factors such as differences in vaccination coverage in future analyses.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Note. The views expressed in this article are those of the authors and not necessarily those of the CDC.

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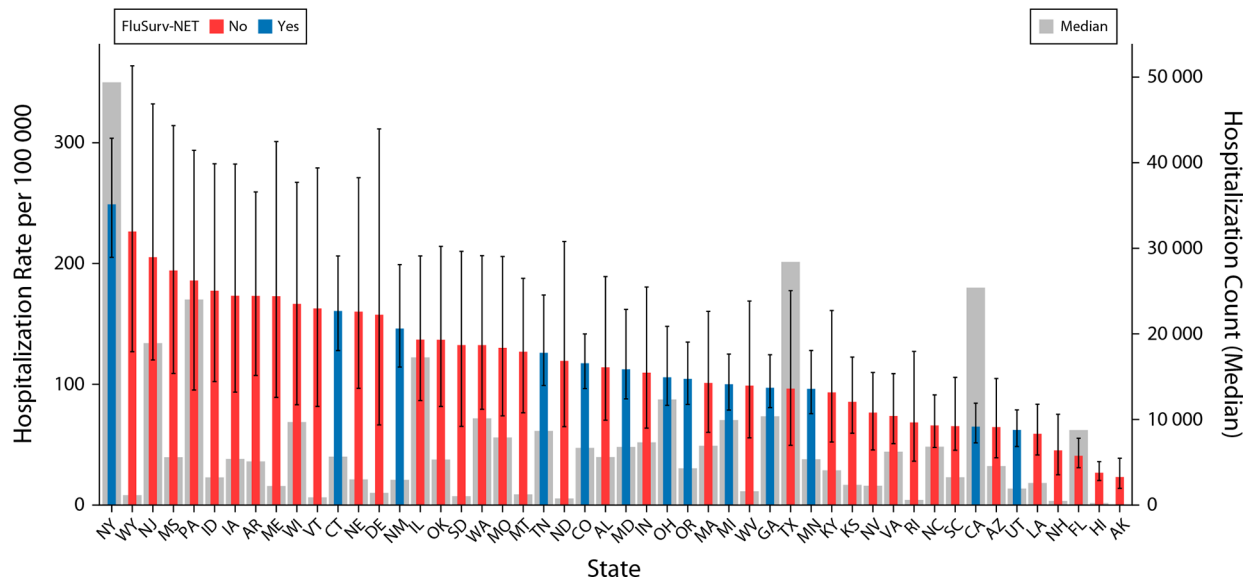


FIGURE 1—. Median Cumulative Influenza-Related Hospitalization Rates From Our Bayesian Model, With FluSurv-NET and Non-FluSurv-NET State Rates: United States, October 2022–April 2023

Note. Whiskers indicate 90% credible intervals. The bar graph is ordered by median value for cumulative influenza-related hospitalization, which cannot be interpreted without intervals.

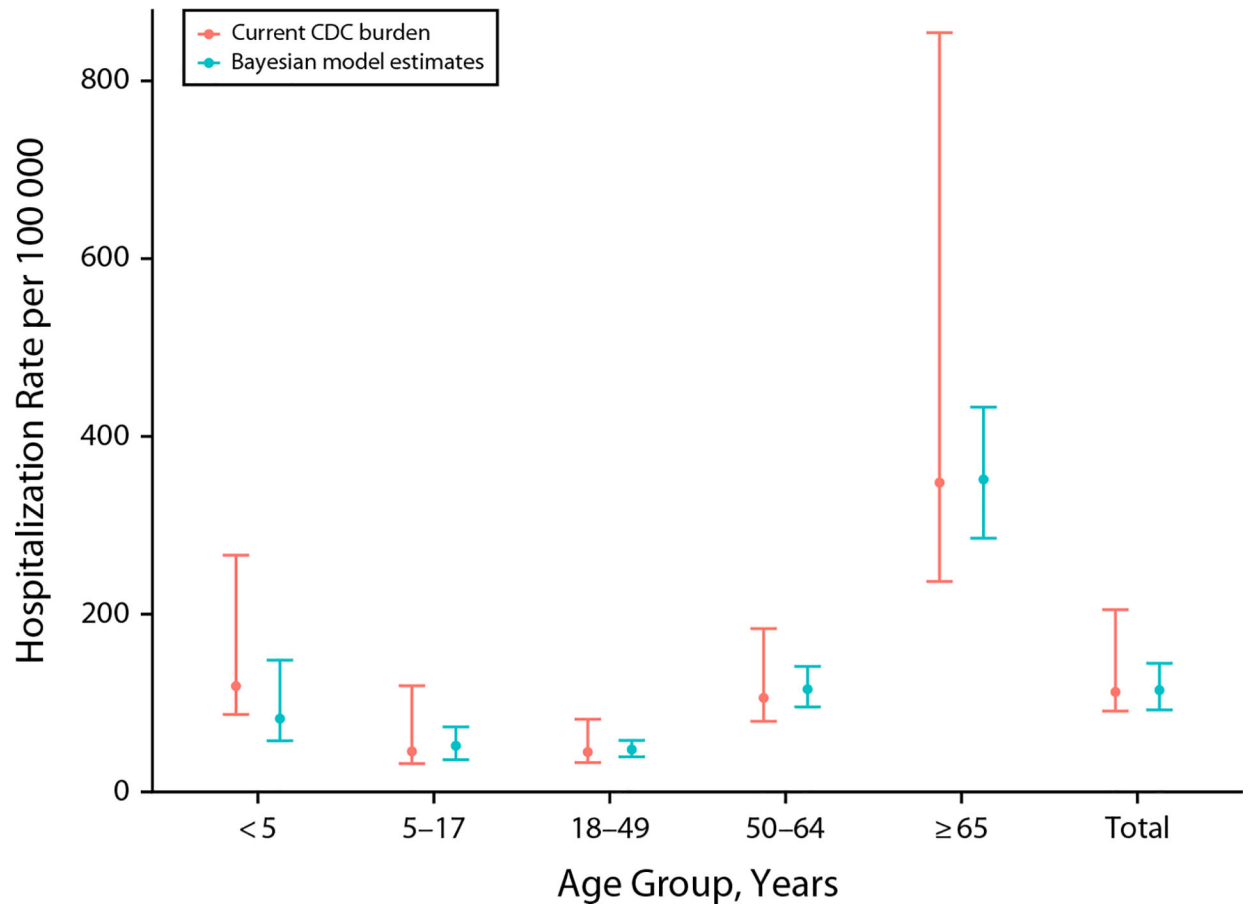


FIGURE 2—. Comparison of Influenza-Related Hospitalization Rates From Our Bayesian Model With the Current Centers for Disease Control and Prevention (CDC) Published Burden, Aggregated by Age Groups: United States, October 2022–April 2023

Note. Whiskers indicate 90% credible intervals from our Bayesian model and 95% uncertainty intervals from the CDC published burden.

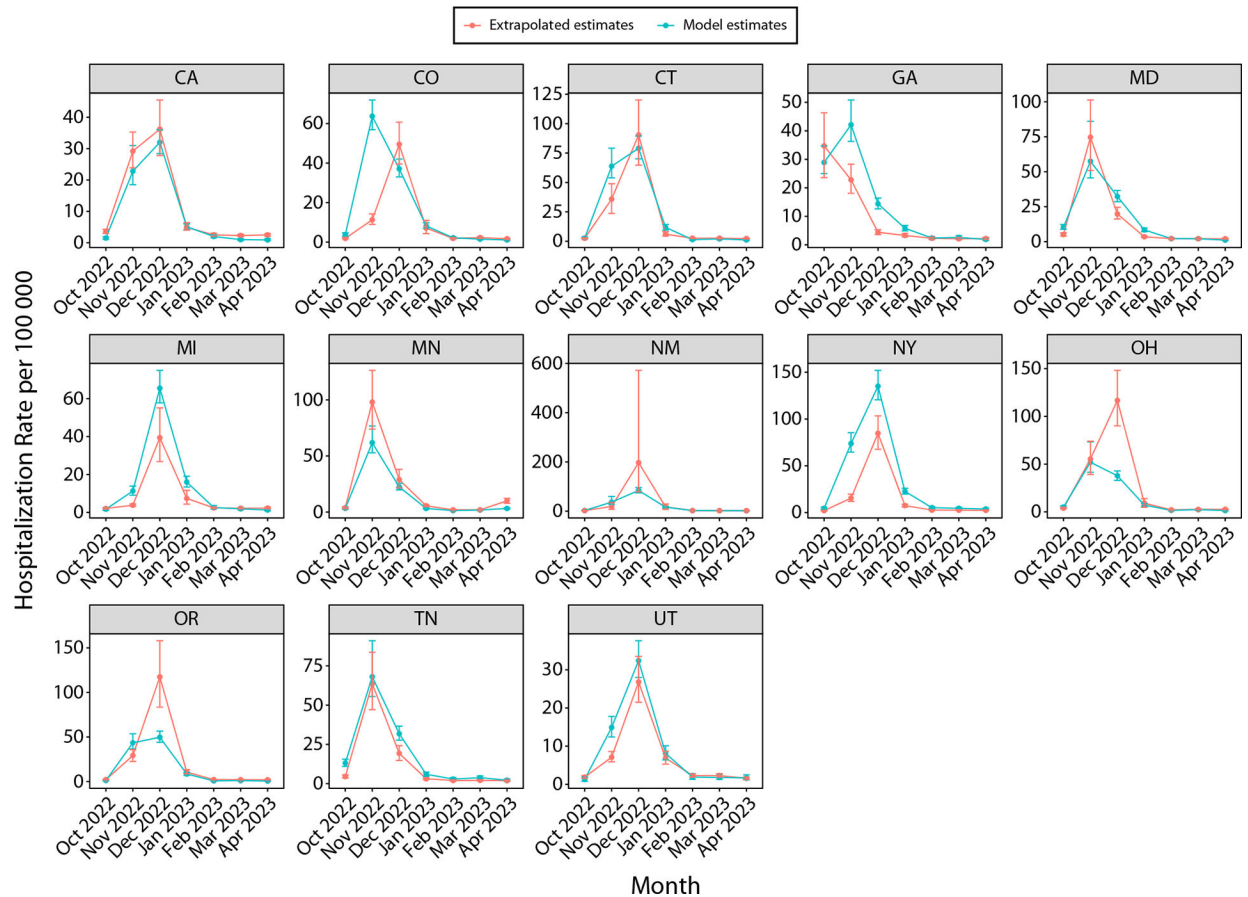


FIGURE 3.— Comparison of Influenza-Related Hospitalization Rates From Our Bayesian Model for Each State in FluSurv-NET Showing the Final Rate From the Model and the Extrapolated Rate When the State Was Not Inputted in the Model: United States, October 2022–April 2023
Note. Whiskers indicate 90% credible intervals.

TABLE 1—

Cumulative Influenza-Related Hospitalization Count and Rate by Age: United States, October 2022–April 2023

Age Group, y	Hospitalization Count, Median (90% CrI)	Hospitalization Rate per 100 000 (90% CrI)
<5	15 500 (10 800, 27 800)	82.4 (57.6, 148.2)
5–17	28 300 (19 800, 40 000)	51.9 (36.2, 73.1)
18–49	66 000 (54 600, 80 200)	47.7 (39.5, 58.0)
50–64	73 500 (60 900, 89 800)	115.1 (95.7, 141.2)
65–74	86 400 (69 300, 108 700)	251.0 (206.0, 323.3)
75–84	72 400 (59 700, 87 000)	447.3 (368.7, 537.4)
≥ 85	37 300 (30 300, 45 800)	625.2 (507.4, 768.0)
Total	379 300 (305 400, 479 300)	114.5 (92.2, 144.7)

Note. CrI = credible interval. Data are from our Bayesian model.