An Agent-Based Model of Seasonal Influenza in a Small-Scale Campus Setting Under Varying Student Vaccination Rates

By

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Abstract

Objectives: College campuses frequently experience high rates of seasonal influenza transmission, posing a risk not only to students but also to the older, more vulnerable faculty and staff who share these indoor environments. This study aims to examine how varying levels of student influenza vaccine uptake impact the transmission dynamics of mild, moderate, and severe influenza strains across the entire campus community in a small-scale, indoor setting.

Methods: We developed an agent-based model (ABM) using the EMOD-Generic software to simulate seasonal influenza transmission within a closed, randomly mixing population of 1,000 agents representing students, faculty, and staff. Demographics and baseline vaccination rates were derived from real-world data. Twelve outbreak scenarios, combining three levels of influenza strain severity and four levels of vaccination, were each simulated 500 times. Primary outcomes included cumulative incidence, peak prevalence, and outbreak duration.

Results: Increasing student vaccination consistently reduced the magnitude and duration of epidemics across all strain severities. In moderate strain scenarios, increasing student vaccination from low (23.4%) to high (46.8%) reduced the median cumulative incidence for the overall population from 39.5% to 26.5%. Notably, despite holding faculty and staff vaccination rates constant, greater student vaccine uptake conferred substantial indirect protection; median cumulative incidence among non-students declined from 37.2% under low student vaccination to 27.7% under high student vaccination in moderate strain epidemics. Peak prevalence and outbreak duration also saw marked reductions as student vaccination increased.

Discussion: Our model showed that higher student influenza vaccine uptake may significantly mitigate cumulative incidence and peak prevalence of influenza for the entire campus community, providing crucial indirect protection to faculty and staff. These findings underscore the critical need for targeted public health interventions to improve student vaccine uptake in higher education settings.

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Introduction

Influenza (flu) is an infectious respiratory disease caused by influenza viruses A, B, C, and D. Influenza A and influenza B are the agents responsible for annual influenza epidemics (seasonal influenza), which typically peak between December and February in the United States (CDC, 2025b). The full flu season lasts from the beginning of October through the end of April in the Northern Hemisphere (CDC, 2024a). Influenza is transmitted person-to-person primarily via large-particle droplets or aerosols (Ijaz et al., 2025). Fomite transmission via contaminated surfaces is another possible transmission pathway, though less prevalent (CDC, 2024a). Influenza can cause mild to severe illness depending on the individual and the virus strain (CDC, 2025b). Symptoms include fever, cough, sore throat, body aches, and fatigue, and illness typically lasts four to seven days (WHO, 2025). During seasons when severe viral strains dominated, influenza has historically been associated with more than one million hospitalizations and 50,000–100,000 deaths in the United States (CDC, 2019a, 2023; Elflein, 2025). Adults ages 65 years and older are at greatest risk of adverse outcomes. Other groups prone to more serious illness include children under 5 years old, pregnant people, and those with chronic medical conditions (WHO, 2025). Since the 2010–2011 flu season, the Centers for Disease Control and Prevention (CDC) has recommended that everyone over six months of age receive an influenza vaccine annually. Seasonal influenza vaccines are developed, based on surveillance of viral activity and predictive models, to target the most common influenza viruses of the year (CDC, 2024c). Vaccination reduces one's risk of getting the flu, and recent evidence suggests vaccination can attenuate the course of disease among those who experience breakthrough infections (CDC, 2025a; Ferdinands et al., 2021).

Like other congregate settings, college/university campuses frequently experience high rates of influenza transmission as a result of high population density and interaction between individuals (Buchsbaum et al., 2022; Lewis et al., 2023; NFID, 2016; Zivich et al., 2020). While the CDC estimates (using models based on hospitalization and census data) the median annual incidence of influenza among 18–49 year olds during the 2010–11 through 2024–25 seasons was 7.9% (CDC, 2019b, 2025b), a far greater proportion of college students report getting the flu. Of the 20,623 students surveyed in the Fall 2025 National College Health Assessment III (NCHA III), 13.5% said a healthcare professional diagnosed them with influenza in the past year (ACHA, 2026, p. 59). Nearly half of students who had the flu said it negatively impacted their performance in a class, and 3.9% said it delayed their progress towards a degree (ACHA, 2026, p. 62). When compared to other upper respiratory infections in a study of 497 students at the University of Washington, influenza-like illness was associated with greater odds of missing work (OR = 2.9), missing class (OR = 3.4), performing poorly on assignments and exams (OR = 1.8), and having high interference with daily life (OR = 6.0) (Emanuels et al., 2019). Influenza also represents a significant health threat to non-student members of campus communities. The higher education workforce skews older than the overall working population (McChesney & Bichsel, 2020; U.S. Bureau of Labor Statistics, 2025), and the unique social mixing dynamics in campus settings facilitate close contact across age groups (Buchsbaum et al., 2022; NFID, 2016; M. Wang, 2017). University faculty and staff therefore represent a population at heightened risk of contracting influenza and experiencing severe outcomes.

Critically, influenza vaccination uptake among college students is consistently well below the coverage threshold for herd immunity, which is approximately 57% given typical virulence (R_0 = 1.4) and vaccine effectiveness (CDC, 2025d; NFID, 2016; Orenstein, 2018). Just 43% of the

20,623 students surveyed in the Fall 2025 NCHA III reported receiving a flu vaccine in the preceding twelve months (ACHA, 2026). This is the continuation of an overall downward trend in flu vaccination since Fall 2020 (Figure 1). Given that students make up the majority of campus populations and exhibit the highest rates of social mixing, their vaccination behavior has a large impact on outbreak dynamics (Ibuka et al., 2016; Kwok et al., 2014; Leung et al., 2017; Y. Liu et al., 2020; Zivich et al., 2020). Raising vaccination rates among students could significantly decrease the incidence of influenza across the campus community, reducing the likelihood that faculty and staff, who tend to be older and at higher risk for adverse outcomes, acquire infection. We developed an agent-based model (ABM) to study the effects of altering student vaccination uptake in student (target) and non-student (non-target) populations in an indoor campus setting.

Methods

The model was created using EMOD-Generic, an agent-based modeling software developed by the Institute for Disease Modeling, part of the Gates Foundation (Institute for Disease Modeling, 2025b). A detailed model description following an abbreviated version of the ODD (Overview, Design concepts, Details) protocol appears in the appendix (Grimm et al., 2006, 2020). Key model components are summarized here. Design concepts outlined by Grimm et al. are italicized in the text for emphasis.

Model Purpose

The purpose of the model is to examine how different levels of student vaccine uptake impact the transmission of seasonal influenza strains of varying infectiousness in a small-scale,

indoor campus setting. It is estimated that humans spend about 90% of their time indoors (Horve et al., 2020). Indoor environments are where the vast majority of close-contact interactions take place, and poor ventilation indoors as compared to outdoors means individuals are more likely to experience sustained exposure to infectious doses of respiratory pathogens like influenza (Barron, 2023). Table 1 includes the full list of vaccination and strain scenarios simulated.

The most important design concepts of the model are *interaction* and *stochasticity*. The shape, scale, and duration of the simulated epidemics arise from the stochasticity encoded in the processes of exposing other agents to infection, acquiring and recovering from infection, and deciding to be vaccinated. Random agent interaction and stochasticity in infectivity are intended to represent random chance in real-world contact networks and capture the uncertainty of influenza virus transmission. Stochasticity in the duration of the incubation and infectious periods attempts to capture variability in disease course without modeling the causes of that variability at the level of individual immune response. And stochasticity in vaccine uptake represents uncertainties about the cognitive, psychological, and social reasons people do or do not receive flu vaccinations.

Three key patterns were used as criteria to evaluate the model's suitability for this purpose. Our interest was in face validity, or the extent to which the model appears to accurately represent the real-world processes it is intended to simulate based on qualitative assessment. Quantitative calibration was not possible because empirical data on the target system (i.e., highly detailed seasonal influenza transmission data from a population of students, faculty, and staff in a small indoor setting on a university campus) were not available. First, we compared the simulated epidemic curves to those of real-world influenza outbreaks in university settings. Epidemic curves documented in the literature are unimodal with a duration of approximately

50–60 days (Guh et al., 2011; Iuliano et al., 2009; Layde et al., 1980; Lewis et al., 2023; Sobal & Loveland, 1982). Second, we checked whether seasons with more severe viral strains were characterized by higher incidence (Biggerstaff et al., 2014, 2018; Budd et al., 2017; CDC, 2024d, 2024e; Jayasundara et al., 2014; Somes et al., 2018; Tokars et al., 2018). Third, we examined whether transmission was inversely related to overall vaccination rate (CDC, 2025a, 2025d; Flannery et al., 2019; Orenstein, 2018; Plans-Rubió, 2012; Rolfes et al., 2019).

Model Design

The model simulates the transmission of seasonal influenza within a randomly mixing, closed population of 1,000 agents. Each agent represents an individual person attending class or working on campus whose implicit motivation is to avoid illness. Agents are assigned an age group (18–49 years, 50–64 years, or 65 years and older) and role (student, faculty, or staff) attributes to reflect relevant variation in vaccination behavior in a population similar to that of Brown University. The age categories in the model align with those typically used by the CDC in relation to influenza because of clinically significant differences in disease course (Budd et al., 2017; Rolfes et al., 2018). Table 2 shows the marginal and conditional distributions of age and role used to calculate the joint distribution of the "AgeRole" attribute assigned to each agent. The marginal distribution of roles is based on university-wide statistics published by the Office of Institutional Research (Brown University, 2023, 2025b). In accordance with those data, all students are assumed to be in the youngest age group (2025b). The conditional distribution of age among faculty is based on the demographics of U.S. professors (McChesney & Bichsel, 2020; TIAA Institute, 2018), and the conditional distribution of age among staff is based on data about higher education employees from the U.S. Bureau of Labor Statistics (2025). This yields a joint AgeRole distribution of 65.0% students aged 18–49 years, 5.9% faculty aged 18–49 years,

14.9% staff aged 18–49 years, 3.9% faculty aged 50–64 years, 7.2% staff aged 50–64 years, 1.2% faculty aged 65 years and older, and 1.9% staff aged 65 years and older.

Approximately 2% of the population is randomly initialized in an infected state. This initial prevalence value was chosen because the U.S. Influenza Surveillance System uses a 2% positivity rate in its sentinel laboratory network as the threshold for elevated influenza activity (CDC, 2025e). All other agents start as susceptible and unvaccinated. Time advances in discrete, one-hour time steps during which agents randomly interact, potentially acquire infection, and move through disease states (if applicable). The model runs for 5,088 time steps (212 days), the length of time between the beginning of October and the end of April, which is considered flu season in the Northern Hemisphere (CDC, 2025b). However, the simulation timeline does not map onto specific calendar dates; the start time could be any point during the flu season when incidence reaches the 2% activity threshold.

Parameterization of Influenza

Influenza is modeled as an SEIR-type pathogen, meaning agents occupy one of four states in relation to the virus: susceptible, exposed, infected, or recovered. When an infected agent and a susceptible agent come into contact, the susceptible agent possibly becomes exposed and is assigned an incubation period based on a random draw from a Poisson distribution with a mean of two days. This distribution was chosen in accordance with World Health Organization guidance (2025), Lessler et al.'s systematic review of published estimates (2009), and Carrat et al.'s review of volunteer challenge studies (2008), which suggest the incubation period is two days on average but ranges from one to four days depending on the individual. Symptoms deterministically appear one day after the agent transitions from exposed to infected (Carrat et al., 2008; WHO, 2025).

Different infectious period distributions and R_0 values characterize the mild, moderate, and severe strain scenarios (Table 3). An agent's infectious period is the timeframe, in days, during which they can transmit disease to others. The population distribution of influenza infectious periods follows a Poisson distribution, as illustrated by Carrat et al.'s review of volunteer challenge studies (2008). Base infectivity is the average number of individuals per day who will be exposed to infection by one infectious individual. In the mild strain scenario, R_0 is set to 1.2, around the 25th percentile of seasonal influenza reproduction numbers calculated in a systematic review by Biggerstaff et al. (2014). The mean infectious period is set to four days, the average for influenza B in Carrat et al.'s review (2008). In the moderate strain scenario, R_0 is set to 1.4, around the 75th percentile of seasonal influenza reproduction numbers calculated by Biggerstaff et al. (2014). The mean infectious period is set to five days, the average for influenza A/H1N1 in Carrat et al.'s review (2008). In the severe strain scenario, R_0 is set to 1.6. This R_0 value is in the fourth quartile of reproduction numbers for seasonal influenza (Biggerstaff et al., 2014). The mean infectious period is set to six days, which is frequently cited as on the high end of illness duration (CDC, 2025b; WHO, 2025).

Parameterization of Vaccination

In the nine scenarios with vaccination (Table 1), flu vaccines are administered in eight weekly distributions beginning at time 0. The three scenarios with no vaccination serve as baselines. Based on studies by the CDC and independent research teams of the past 20 flu seasons, vaccine effectiveness at preventing infection is standardized at 50% (CDC, 2025d). Each agent may be vaccinated once per season.

Faculty and staff vaccine uptake is constant by age group across vaccination scenarios, while student vaccine uptake varies. A specified proportion of the unvaccinated population is

randomly selected for vaccination at each distribution. Since the population of eligible agents shrinks with each distribution, the number of agents vaccinated decreases over time. Additionally, small population size, particularly of faculty and staff, introduces considerable variation in overall coverage. The target rates for faculty and staff are based on vaccine uptake among adults in Rhode Island: 46.8% among those 18–49 years old, 59.6% among those 50–64 years old, and 79.5% among those 65 or more years old (KFF, 2024). The per-distribution demographic coverage was calculated for each AgeRole as follows:

$$Demographic\ coverage\ =\ 1\ -\ (1\ -\ target\_rate)^{\frac{1}{8}}$$

Weekly demographic coverage probabilities are provided in Table 4. Under low student uptake, the seasonal target rate for students is 23.4%, half that of non-students ages 18–49 years. Under medium student uptake, the seasonal target rate for students is 46.8%, equal to that of non-students ages 18–49 years, requiring a 7.6% weekly demographic coverage probability. Under high student uptake, the seasonal target rate is 70.2%, 1.5 times that of non-students ages 18–49 years.

Outputs

Twelve outbreak scenarios, each based on a combination of strain severity and vaccine uptake (Table 1), were modeled in 500 simulation runs apiece. The final data set included 30,528,000 hourly observations. The key model outputs used for analyses were: the number of new infections per time step, used to sum cumulative incidence; the time step at which transmission dropped to zero through the end of the simulation, used to calculate the outbreak duration; and the number of infected agents per time step, used to calculate peak prevalence.

These data were derived from the default and attribute-based output files produced by EMOD-Generic for each simulation.

Analysis

Simulation data was parsed, cleaned, analyzed, and summarized in R. Our analysis plan consisted of three parts. First, the results of each simulated outbreak were analyzed by scenario. Cumulative incidence was calculated as the sum of new infections at each time step over the course of the 212-day simulation. Peak prevalence was defined as the maximum infected population in a single time step, or the greatest number of individuals who had influenza at one time. The time step at which the epidemic died out was divided by 24 to calculate the outbreak duration in days. Vaccination rates for each AgeRole were calculated by dividing the number of vaccinated agents in the subpopulation at the last time step by the total number of agents in the subpopulation. The median and 95% simulation interval were calculated for each outcome. Simulation intervals capture the central range of outcomes observed across many model runs, helping to quantify uncertainty.

Second, the results calculated from each scenario were aggregated to examine outcomes in the overall population. Each scenario's 500 epidemic curves were plotted by summing new infections per day (Figure 2). The distributions of cumulative incidence, peak prevalence, and outbreak duration were visualized using boxplots.

Third, subgroup analysis was employed to assess whether infection rates differed between students (the targets of vaccine uptake interventions) and faculty and staff (not the targets of vaccine uptake interventions). The median and 95% simulation intervals for cumulative incidence and vaccination rate were calculated among students and non-students. The same statistics were also calculated for AgeRole subpopulations. Outcome distributions for

students versus non-students and students versus non-students by age group were visualized using boxplots.

Results

Strain Severity

The no vaccination scenarios were used to isolate the effects of altering strain severity. Across 500 simulations per strain scenario, consistent patterns emerged in relation to severity (Table 5). Under no vaccination, cumulative incidence increased with strain severity, from a median of 37.1% in mild strain outbreaks to 53.5% in moderate strain outbreaks and 65.7% in severe strain outbreaks. Peak prevalence followed a similar pattern, ranging from 5.4% for the mild strain to 14.6% for the severe strain. Median outbreak duration was higher for the moderate strain (91 days) than for the mild (85 days) or severe (88 days) strains. These results confirm that strain severity substantially influenced the magnitude and duration of epidemics, as we intended with parameterization.

Vaccination by Strain Severity

Figure 2 shows the epidemic curves of 6,000 outbreaks simulated across twelve scenarios. Tables and plots of the distribution of vaccine uptake by subpopulation are included in the model protocol. As expected based on epidemic curves available for seasonal and pandemic influenza on college campuses, the simulated epidemics were generally unimodal, characterized by a rapid rise in infections, a peak within the first 50 days, and a long right tail after transmission died out (Guh et al., 2011; Iuliano et al., 2009; Layde et al., 1980; Lewis et al., 2023; Sobal & Loveland, 1982).

Table 6 summarizes epidemic outcomes under varying levels of vaccine uptake and strain severity. Increasing student vaccination consistently reduced cumulative incidence (Figure 3), peak prevalence (Figure 4), and outbreak duration (Figure 5) across strain severity scenarios. For example, in moderate strain scenarios, the median proportion of the population infected over the course of a season decreased from 39.5% under low student vaccination to 33.5% under medium vaccination to 26.5% under high vaccination. Similar trends were observed across mild and severe strain scenarios. On average, medium student vaccination reduced total infections by approximately 14% relative to low student vaccination, and high student vaccination reduced total infections by approximately 18% relative to medium student vaccination. Raising student vaccination rates had the greatest impact on cumulative incidence in the moderate strain scenarios. On the other hand, the reduction in peak prevalence is most pronounced in the severe strain scenario and least pronounced in the mild strain scenario. For instance, in severe strain scenarios, median peak prevalence decreased from 11.3% to 8.2% under high student vaccination, an approximately 27% decrease. In mild strain scenarios, however, the decrease from low to high student vaccination was 4.3% to 3.8%, around 12%.

Outbreak duration of mild and moderate strain epidemics tended to decrease as vaccination rates increased. For example, in mild strain scenarios, median duration decreased from 68 days under low vaccination to 61 days under medium vaccination to 56 days under high vaccination. Altering vaccination rates did not have as large of an effect on the duration of severe strain epidemics, as median duration was between 85 days and 89 days under all scenarios, including no vaccination. Without vaccination, moderate strain epidemics tended to last longer than severe strain epidemics. With vaccination, duration increases with strain severity.

Students: Table 7 and Figure 6 show the cumulative incidence of influenza among students. Across strain scenarios, higher student vaccination was consistently associated with lower cumulative incidence. In moderate strain scenarios, for example, median cumulative incidence declined from 41.3% under low vaccination to 33.6% under medium vaccination to 26.1% under high vaccination. Increasing student vaccination from low to medium reduced cumulative incidence rates among students by approximately 17% on average. Increasing student vaccination from medium to high reduced cumulative incidence rates among students by approximately 21% on average.

Faculty and staff: Table 8 and Figure 7 show cumulative incidence among faculty and staff. Despite constant vaccination coverage in the non-student group, infection risk declined as student vaccination increased. In moderate strain scenarios, median cumulative incidence decreased from 37.2% under low student vaccination to 32.9% under medium student vaccination and 27.7% under high student vaccination. As in the student subpopulation, larger absolute reductions in cumulative incidence occurred in moderate and severe strain epidemics, while the relative impact of increasing vaccination in mild strain epidemics was more modest. These patterns were consistent across faculty and staff age groups (Table 9). Although absolute risk of infection was slightly lower among older groups, the relative reductions associated with greater student vaccine uptake were consistent across ages. These results are visualized in Figure 8, Figure 9, and Figure 10.

Discussion

The results of our simulated epidemics demonstrate the indirect impact of student vaccination on influenza transmission dynamics in indoor, campus settings. Higher student

vaccine uptake significantly reduced cumulative incidence and peak prevalence in the entire campus community, particularly when rates were higher than the 18–49 age group average. There were also modest reductions in epidemic duration in mild and moderate strain outbreaks.

The role of college/university student vaccination is particularly important in light of shifting attitudes towards vaccines in the United States. Research by behavioral and social scientists shows that, although vaccine hesitancy and anti-vaccine sentiment have become more entrenched within certain ideological subgroups, the SARS-CoV-2 pandemic decreased influenza vaccine hesitancy overall (Skyles et al., 2024). For example, a study conducted at the University of Rhode Island in 2020 found that 53% of students were more likely to receive the influenza vaccine as a result of the pandemic (Silva et al., 2021). But, while COVID-19 may have raised awareness about the importance of vaccination, convenience and low perceived risk to self remain the primary barriers to influenza vaccination among college students (NFID, 2017; Ryan et al., 2019; Skyles et al., 2024). These barriers underscore the potential of targeted interventions to improve student vaccination rates (Ryan et al., 2019; Shon et al., 2021; M. Wang, 2017).

The current model is a valuable starting point for investigating influenza transmission dynamics in campus settings, but there are numerous improvements to realism that could be implemented in future iterations. One major limitation to realism is the assumption of random mixing within the population. We see incidence rates much higher than the 3–11% per year estimated for the U.S. population (Tokars et al., 2018). The benefits of student vaccination may be overstated in our model because we assume that students, faculty, and staff interact at the same rate, glossing over variations in contact patterns. For example, students are very likely to interact with other students on a daily basis and very unlikely to interact with faculty members they do not have as instructors on a daily basis. The network sparsity that would result from

groups interacting at different rates would almost certainly reduce the spillover effect of student vaccination. Additionally, the model assumes that all agents have the same base infectivity, which fails to capture natural variability in contagiousness and contact rates between individuals. To better reflect these dynamics, a log-normal distribution for infectivity could be implemented (K. Frey, personal communication, February 9, 2026), allowing for variability in these critical components of reproductive rate (Ajelli & Litvinova, 2017; Kucharski et al., 2014; Mossong et al., 2008; Taube et al., 2025; Zivich et al., 2020).

The model could be expanded to include a masking intervention. Masking behavior could vary by factors such as gender, age, and health status. Studies show, for example, that females are more likely to mask than males (Cassino & Besen-Cassino, 2020; Haischer et al., 2020; Moran & Del Valle, 2016; Ritter & Brenan, 2020), that older people are more likely to mask than younger people (Haischer et al., 2020; E. Liu & Arledge, 2022), and that individuals with chronic health conditions are more likely to mask than the general population (E. Liu & Arledge, 2022).

Another possible improvement would be the inclusion of *adaptation*. Currently, the model assumes fixed behaviors regardless of health status. However, it is reasonable to assume that symptomatic individuals could sense they have the flu and adjust their behavior in response (NFID, n.d.). This could take the form of symptomatic individuals choosing to wear a mask or stay home and self-isolate (Blanchet Zumofen et al., 2023; Fisman et al., 2024). SEIR state sensing would also enable the model to include risk-reducing behaviors, like wearing a face mask or seeking vaccination, based on agents' observation of disease in their network.

Finally, the model has the potential to have a greater degree of spatial and temporal explicitness (Manson et al., 2020). For example, altering transmission potential in response to

university events and recesses could help capture some of the unique epidemic dynamics introduced by the campus schedule and environment setting (Cauchemez et al., 2008; Jackson et al., 2013; Nichol et al., 2010; Qiao et al., 2024).

In conclusion, our results highlight the potentially substantial indirect benefits of student vaccination on influenza transmission in campus settings, underscoring the importance of improving vaccine uptake in this population. Limitations of the model that should be addressed in future iterations include the random mixing assumption and uniform agent infectivity. Incorporating more realistic contact networks, adding adaptive behaviors such as masking and self-isolating, and increasing spatial and temporal resolution would make for a more accurate representation of seasonal influenza transmission. Models like the one we endeavored to create are critical tools for informing infectious disease policies and interventions on college campuses, particularly in an era of emerging pathogenic threats and anti–public health sentiment.

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Tables

Table 1: Seasonal influenza scenarios modeled to assess the effects of student vaccination rates in a small-scale, indoor college/university campus setting.

Category	**Scenario**
Without vaccination	No vaccination, mild strain
	No vaccination, moderate strain
	No vaccination, severe strain
With vaccination	Low student vaccination, mild strain
	Low student vaccination, moderate strain
	Low student vaccination, severe strain
	Medium student vaccination, mild strain
	Medium student vaccination, moderate strain
	Medium student vaccination, severe strain
	High student vaccination, mild strain
	High student vaccination, moderate strain
	High student vaccination, severe strain

Table 2: Demographics used to derive the joint distribution of the "AgeRole" attribute assigned to each agent.

Variable	Level		Proportion	Source(s)
Role	Student		0.65	(Brown University, 2025a)
	Faculty		0.11	(Brown University, 2025a)
	Staff		0.24	(Brown University, 2023)
Age	Student	18–49 years	1.00	(Brown University, 2025a)
	Faculty	18–49 years	0.54	(McChesney & Bichsel, 2020; TIAA Institute, 2018)
		50–64 years	0.35	
		≥ 65 years	0.11	
	Staff	18–49 years	0.62	(U.S. Bureau of Labor Statistics, 2025)
		50–64 years	0.30	
		≥ 65 years	0.08	

Table 3: Agent state attributes and initial distributions.			
Attribute	**Representation**	**Type**	**Value or distribution**
SEIR state	Natural history stage	Categorical (dynamic)	Susceptible
			Exposed
			Infected
			Recovered
Incubation period	Time (in days) between exposure and symptomaticity	Numerical (static)	$X \sim Pois(2)$
Infectious period	Timeframe (in days) during which an infected agent can transmit disease to others	Numerical (static)	Mild: $X \sim Pois(4)$
			Moderate: $X \sim Pois(5)$
			Severe: $X \sim Pois(6)$
Symptomatic	Whether infected agent is symptomatic	Categorical (dynamic)	Symptoms
			No symptoms
Base infectivity	The average number of individuals per day who will be exposed to infection by one infectious individual	Numerical (static)	Mild: 0.300
			Moderate: 0.280
			Severe: 0.267
Intervention status	Vaccination status	Categorical (dynamic)	Vaccinated
			Unvaccinated

Table 4: Target rates and weekly demographic coverage probabilities for vaccination scenarios by age and role.

Student uptake	Age	Target rate	Weekly coverage
Faculty			
All	18–49 years	46.8%	7.6%
	50–64 years	59.6%	9.9%
	≥ 65 years	79.5%	16.0%
Staff			
All	18–49 years	46.8%	7.6%
	50–64 years	59.6%	9.9%
	≥ 65 years	79.5%	16.0%
Students			
Low	18–49 years	23.4%	3.3%
Medium		46.8%	7.6%
High		70.2%	14.0%

Table 5: Median (95% simulation interval) epidemic outcomes from 500 simulations under no vaccination intervention in a closed population of 1,000 agents.

Strain severity	**Cumulative incidence** (%)	**Peak prevalence** (%)	**Outbreak duration** (days)
Mild	37.1% (17.2%, 48.7%)	5.4% (2.8%, 9.0%)	85 (57, 146)
Moderate	53.5% (43.0%, 62.3%)	9.4% (5.8%, 13.8%)	91 (68, 132)
Severe	65.7% (58.4%, 72.3%)	14.6% (10.2%, 19.8%)	88 (71, 119)

Table 6: Median (95% simulation interval) epidemic outcomes from 500 simulations of each vaccination and strain scenario in a closed population of 1,000 agents.

Strain severity	Cumulative incidence	Peak prevalence	Duration (days)
Vaccination uptake: Low			
Mild	23.8% (9.5%, 37.5%)	4.3% (2.2%, 7.8%)	68 (40, 109)
Moderate	39.8% (21.8%, 49.5%)	7.1% (3.6%, 11.3%)	84 (62, 134)
Severe	53.2% (42.2%, 61.5%)	11.3% (6.90%, 15.8%)	89 (70, 134)
Vaccination uptake: Medium			
Mild	20.2% (7.7%, 32.1%)	4.1% (1.9%, 7.3%)	61 (41, 95)
Moderate	33.5% (17.4%, 45.6%)	6.3% (3.3%, 10.5%)	79 (59, 125)
Severe	46.6% (33.4%, 56.7%)	9.9% (5.6%, 15.0%)	88 (66, 132)
Vaccination uptake: High			
Mild	16.4% (6.9%, 28.8%)	3.8% (1.9%, 6.7%)	56 (36, 87)
Moderate	26.9% (11.8%, 39.3%)	5.5% (2.7%, 9.3%)	73 (50, 106)
Severe	39.1% (21.2%, 50.0%)	8.2% (4.3%, 12.8%)	85 (65, 131)

Table 7: Median (95% simulation interval) cumulative incidence (percent infected over the course of the season) among students from 500 simulations of each scenario in a closed population of 1,000 agents.

Strain severity	Cumulative incidence (%)
No vaccination	
Mild	37.2% (17.5%, 48.3%)
Moderate	53.5% (42.4%, 63.1%)
Severe	65.6% (57.9%, 72.3%)
Vaccination uptake: Low	
Mild	24.5% (9.6%, 38.9%)
Moderate	41.3% (22.9%, 52.4%)
Severe	54.8% (43.4%, 63.3%)
Vaccination uptake: Medium	
Mild	20.3% (7.5%, 32.6%)
Moderate	33.6% (17.8%, 46.1%)
Severe	47.2% (32.4%, 57.3%)
Vaccination uptake: High	
Mild	15.9% (6.6%, 28.3%)
Moderate	26.1% (11.7%, 38.6%)
Severe	37.9% (21.0%, 49.1%)

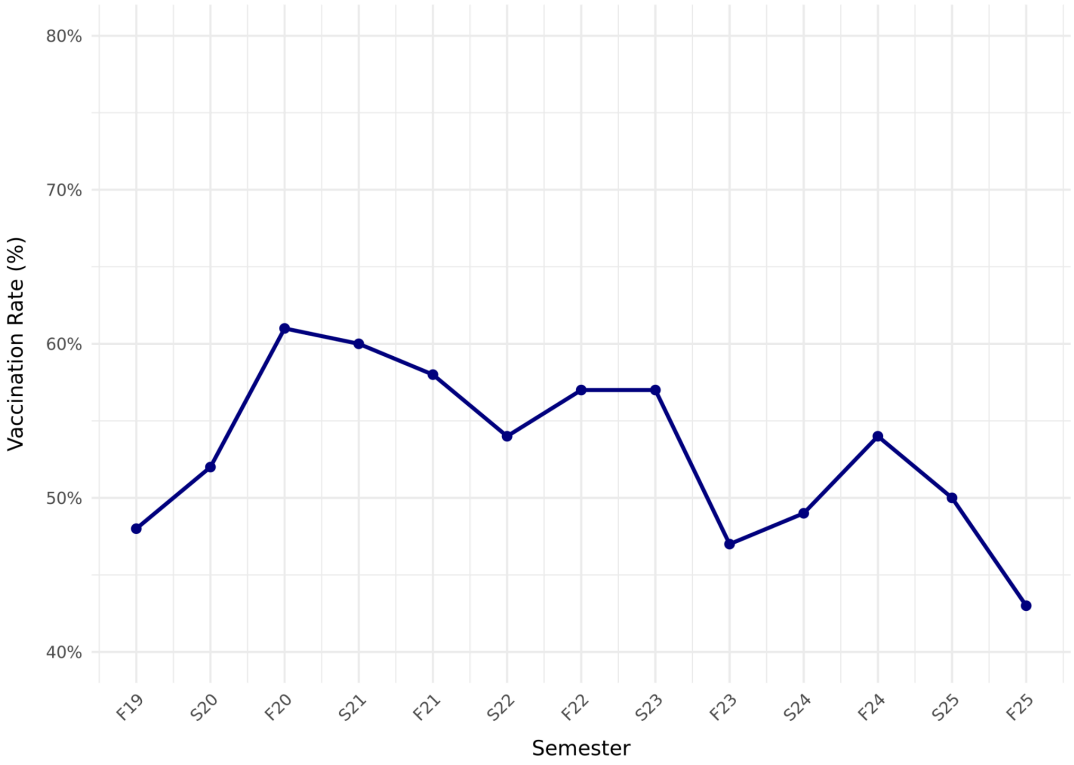
Table 8: Median (95% simulation interval) cumulative incidence rate among faculty and staff from 500 simulations of each scenario in a closed population of 1,000 agents.	
Strain severity	**Cumulative incidence (%)**
No vaccination	
Mild	36.9% (17.0%, 50.3%)
Moderate	53.6% (41.9%, 62.9%)
Severe	65.7% (57.7%, 73.9%)
Vaccination uptake: Low	
Mild	22.5% (8.0%, 36.0%)
Moderate	37.1% (19.8%, 48.0%)
Severe	50.3% (38.8%, 59.4%)
Vaccination uptake: Medium	
Mild	19.6% (7.6%, 33.2%)
Moderate	32.9% (17.0%, 46.3%)
Severe	45.7% (32.7%, 56.0%)
Vaccination uptake: High	
Mild	17.1% (6.8%, 31.1%)
Moderate	28.3% (12.2%, 40.9%)
Severe	40.6% (22.3%, 53.0%)

Table 9: Median (95% simulation interval) cumulative incidence among faculty and staff by age group from 500 simulations of each scenario in a closed population of 1,000 agents.

Strain severity	Cum. incidence (%), 18–49 years	Cum. incidence (%), 50–64 years	Cum. incidence (%), ≥ 65 years
No vaccination			
Mild	36.7% (16.9%, 51.1%)	36.2% (15.2%, 53.8%)	35.7% (11.8%, 59.3%)
Moderate	53.9% (41.0%, 64.1%)	53.3% (39.4%, 64.3%)	53.3% (32.8%, 71.0%)
Severe	65.9% (56.5%, 74.3%)	65.5% (54.6%, 77.1%)	66.7% (44.2%, 84.9%)
Student vaccination uptake: Low			
Mild	23.0% (7.2%, 37.3%)	22.1% (8.3%, 37.0%)	21.4% (3.2%, 42.1%)
Moderate	38.0% (21.8%, 49.6%)	35.8% (18.9%, 50.0%)	33.8% (12.7%, 55.4%)
Severe	51.1% (39.7%, 61.8%)	50.0% (36.1%, 61.1%)	45.2% (24.7%, 63.5%)
Student vaccination uptake: Medium			
Mild	19.7% (7.4%, 33.6%)	18.9% (7.3%, 35.0%)	18.2% (3.0%, 39.3%)
Moderate	33.5% (16.3%, 47.2%)	32.3% (16.2%, 47.1%)	30.0% (9.3%, 49.4%)
Severe	46.9% (32.5%, 57.9%)	45.3% (30.2%, 58.5%)	40.6% (22.4%, 62.1%)
Student vaccination uptake: High			
Mild	17.5% (6.2%, 31.4%)	17.0% (6.5%, 31.5%)	15.6% (2.7%, 35.9%)
Moderate	28.5% (11.5%, 43.9%)	27.5% (11.5%, 43.0%)	25.8% (8.0%, 46.8%)
Severe	41.4% (22.6%, 54.3%)	39.7% (21.1%, 53.9%)	37.0% (13.8%, 57.6%)

Figures

Figure 1: U.S. college student vaccination rate, 2019–2025



F = Fall semester, S = Spring semester. Data were sourced from the Fall 2019 through Fall 2025 editions of the American College Health Association's National College Health Assessment III (ACHA, 2025a, 2025g, 2025b, 2025h, 2025c, 2025i, 2025d, 2025j, 2025e, 2025k, 2025f, 2025l, 2026).

Figure 2: Incidence curves from simulated influenza seasons (500 per scenario) by vaccine uptake and strain severity in a closed population of 1,000 agents. The black line represents the mean daily incidence for a given scenario.

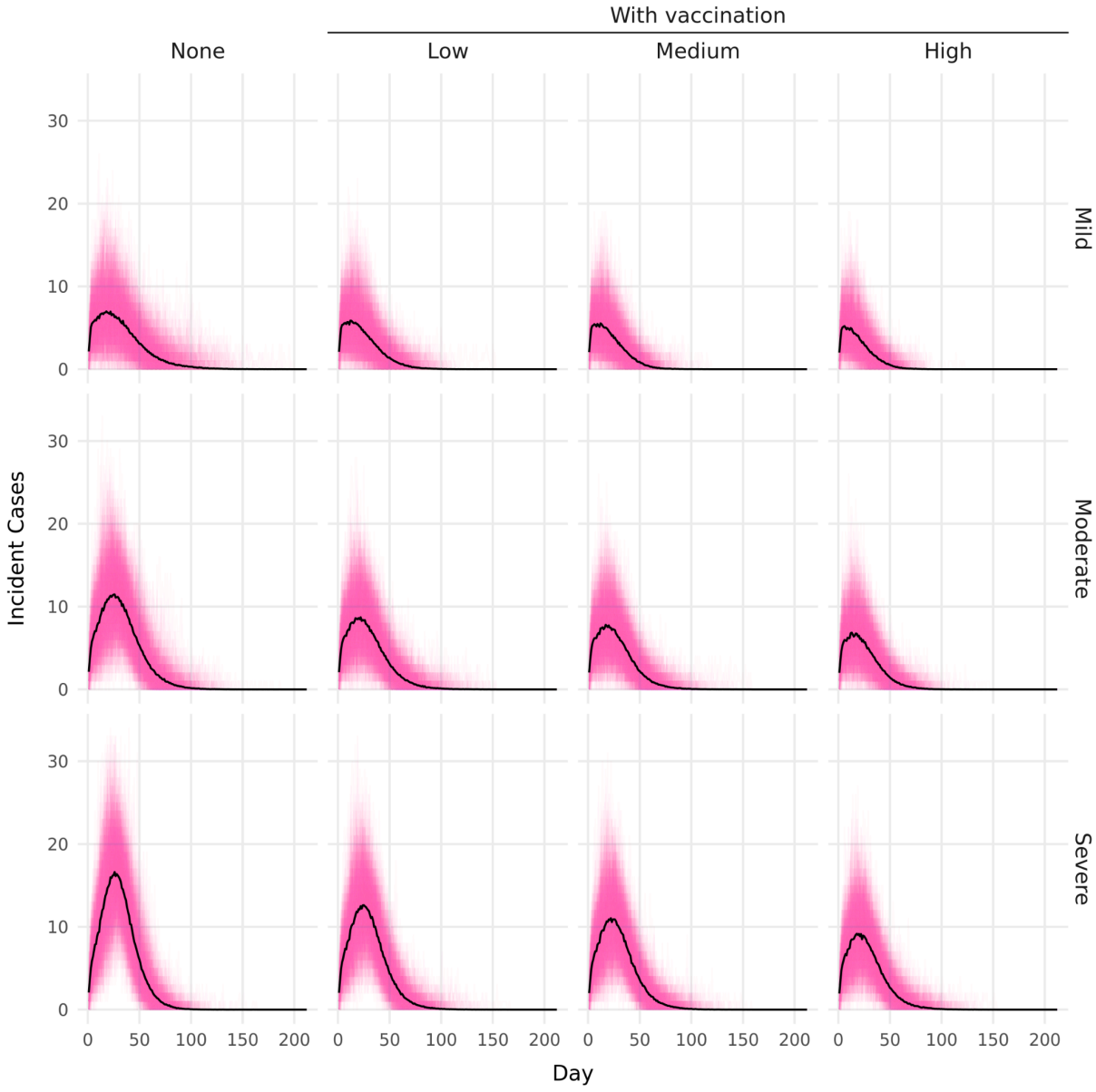


Figure 3: Boxplot of cumulative incidence from simulated influenza seasons (500 per scenario) by vaccine uptake and strain severity in a closed population of 1,000 agents.

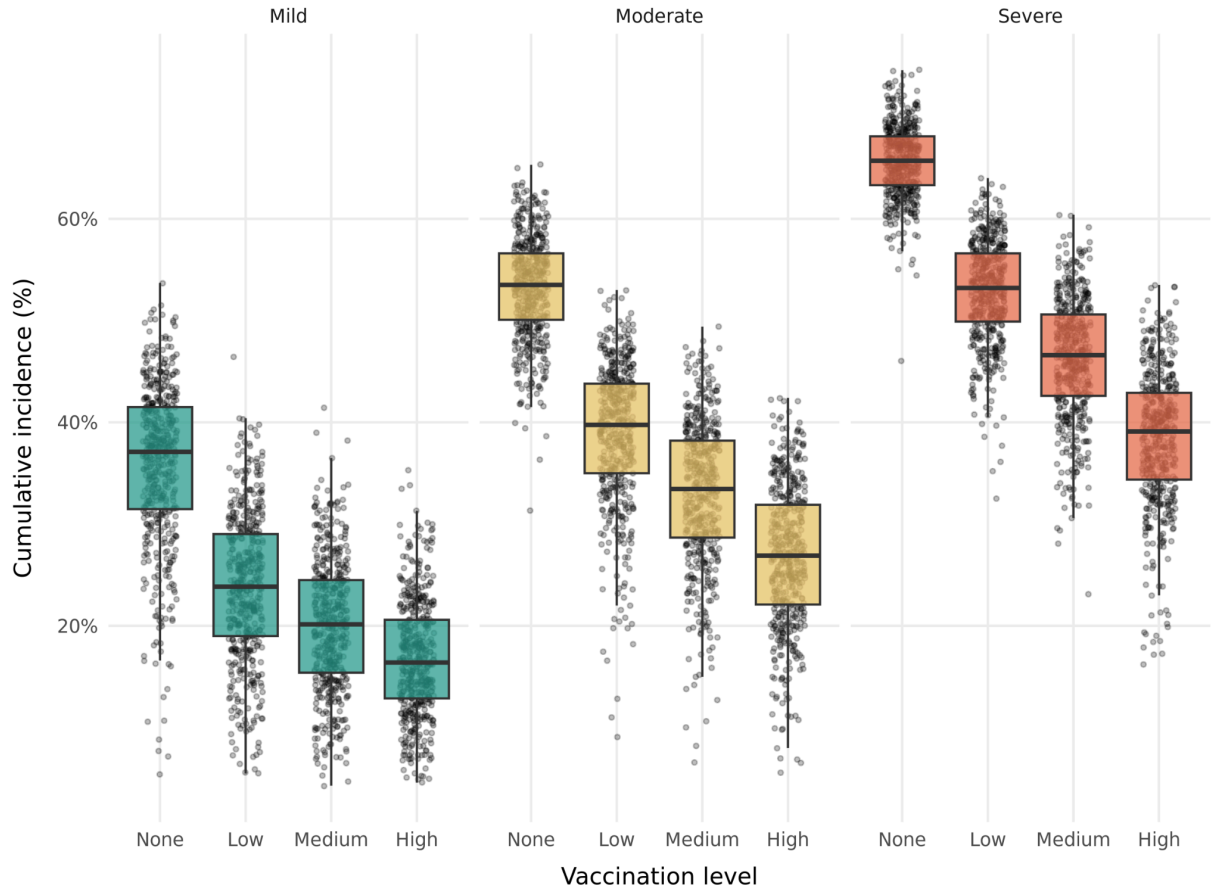


Figure 4: Boxplot of peak prevalence from simulated influenza seasons (500 per scenario) by vaccine uptake and strain severity in a closed population of 1,000 agents.

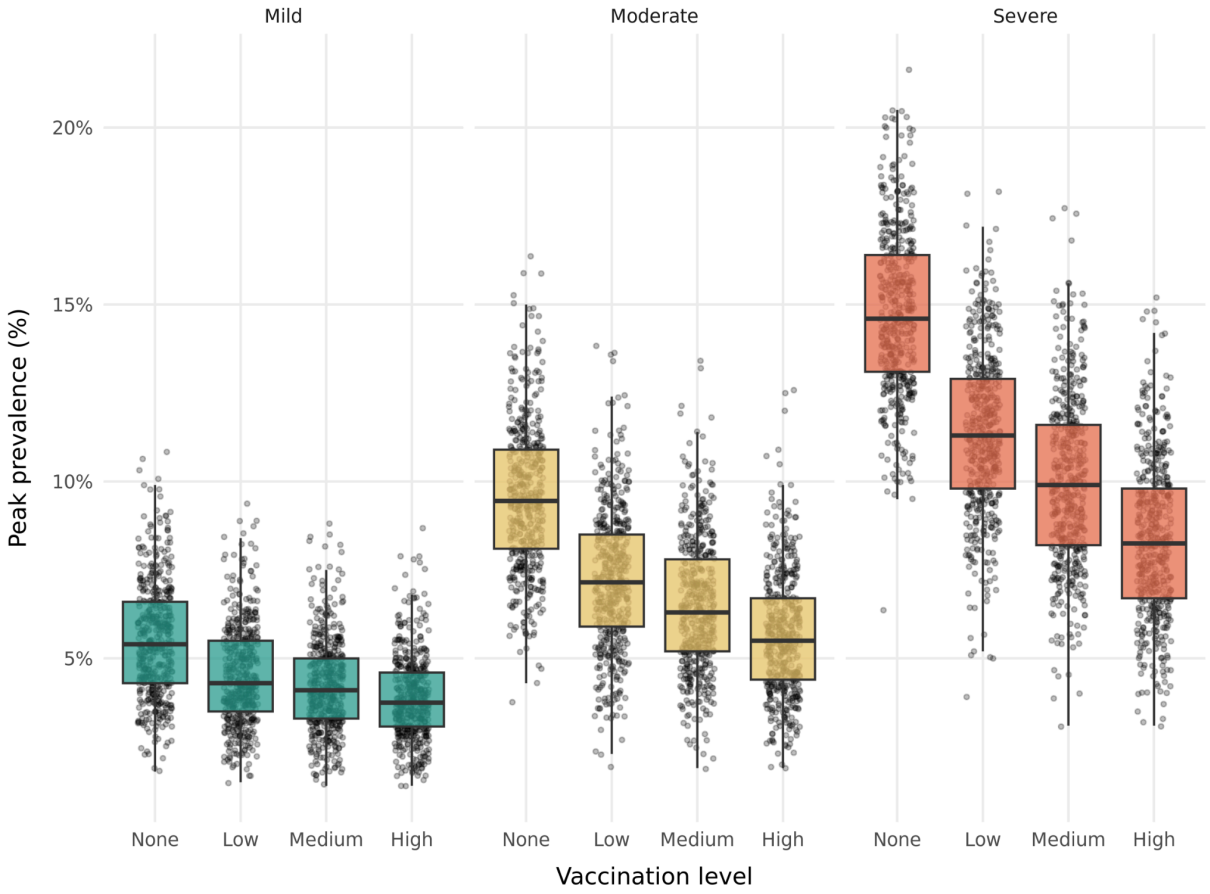


Figure 5: Boxplot of outbreak duration from simulated influenza seasons (500 per scenario) by vaccine uptake and strain severity in a closed population of 1,000 agents.

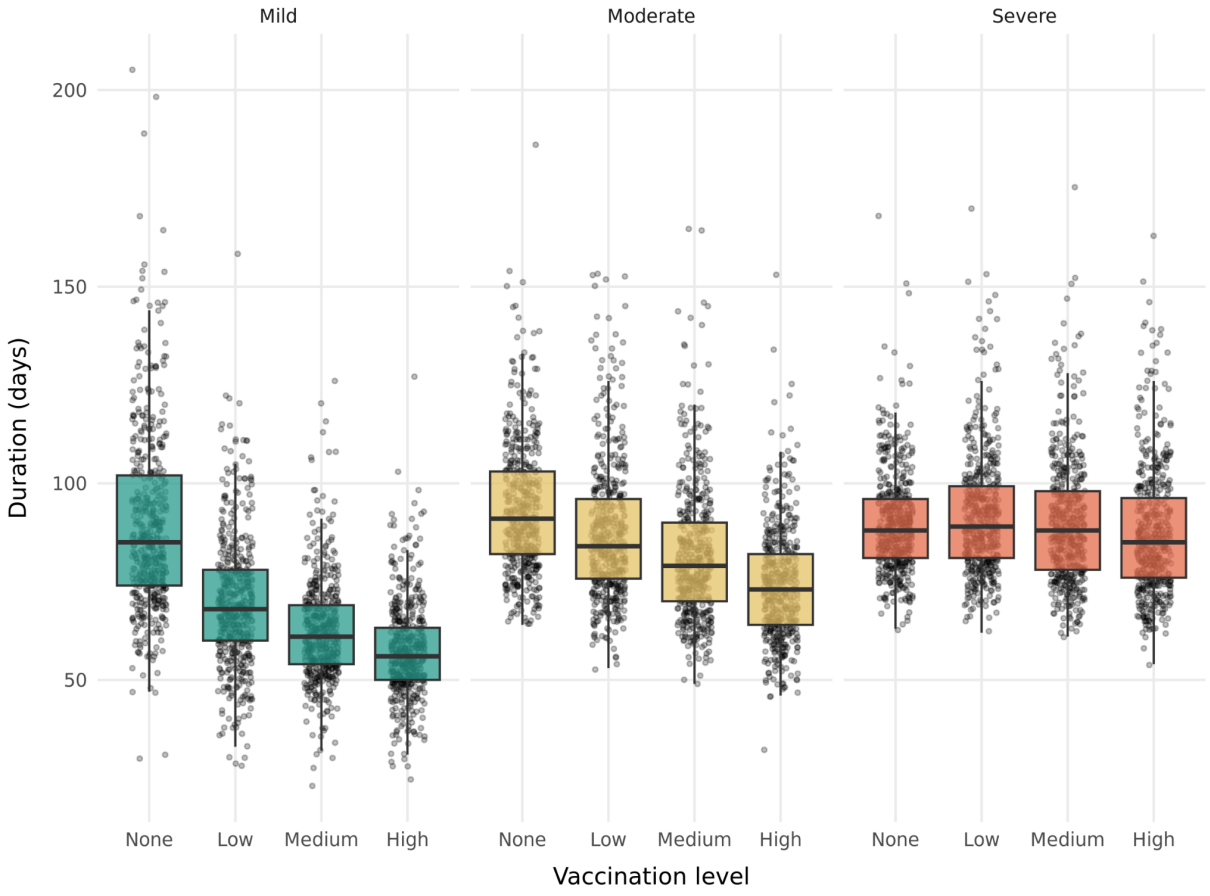


Figure 6: Boxplot of cumulative incidence among students from simulated influenza seasons (500 per scenario) by vaccine uptake and strain severity in a closed population of 1,000 agents.

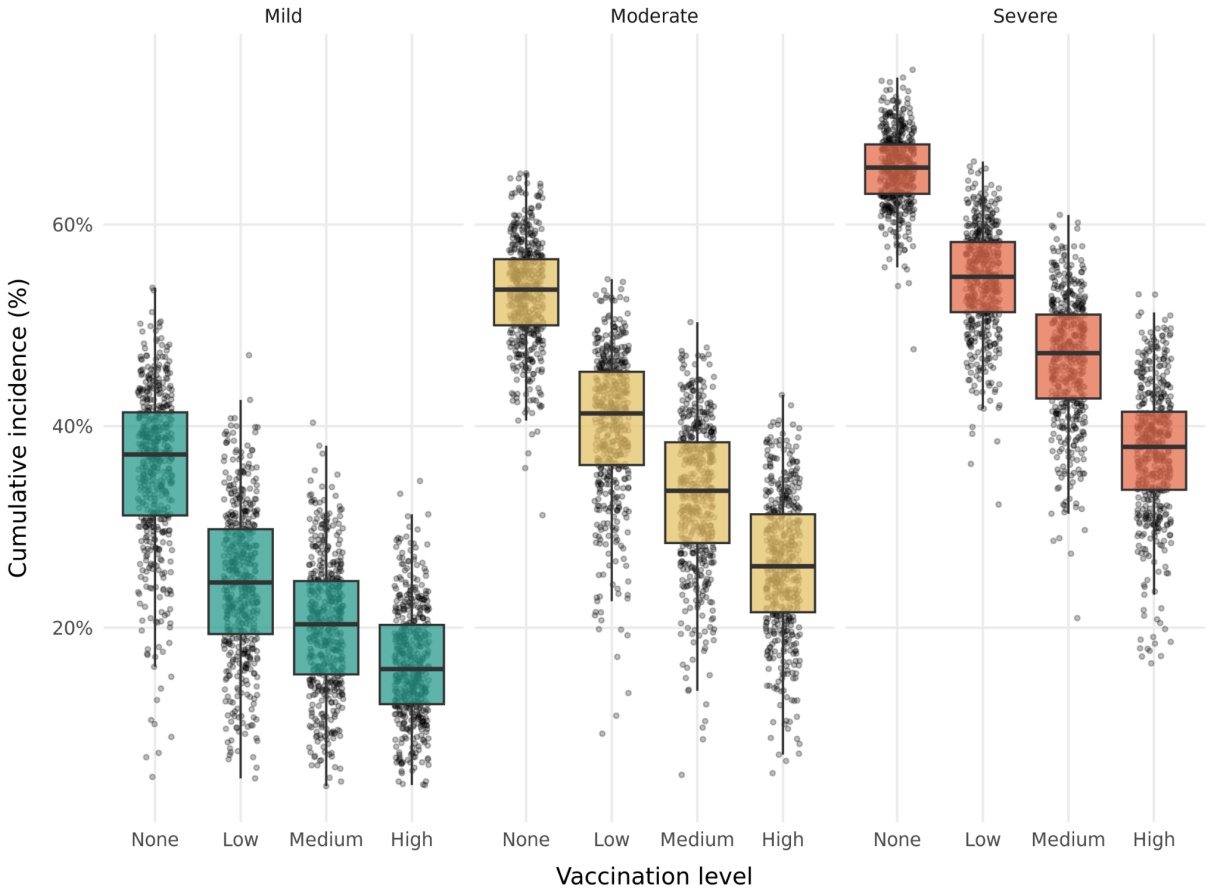


Figure 7: Cumulative incidence of influenza among faculty and staff across 500 simulations per scenario in a closed population of 1,000 agents.

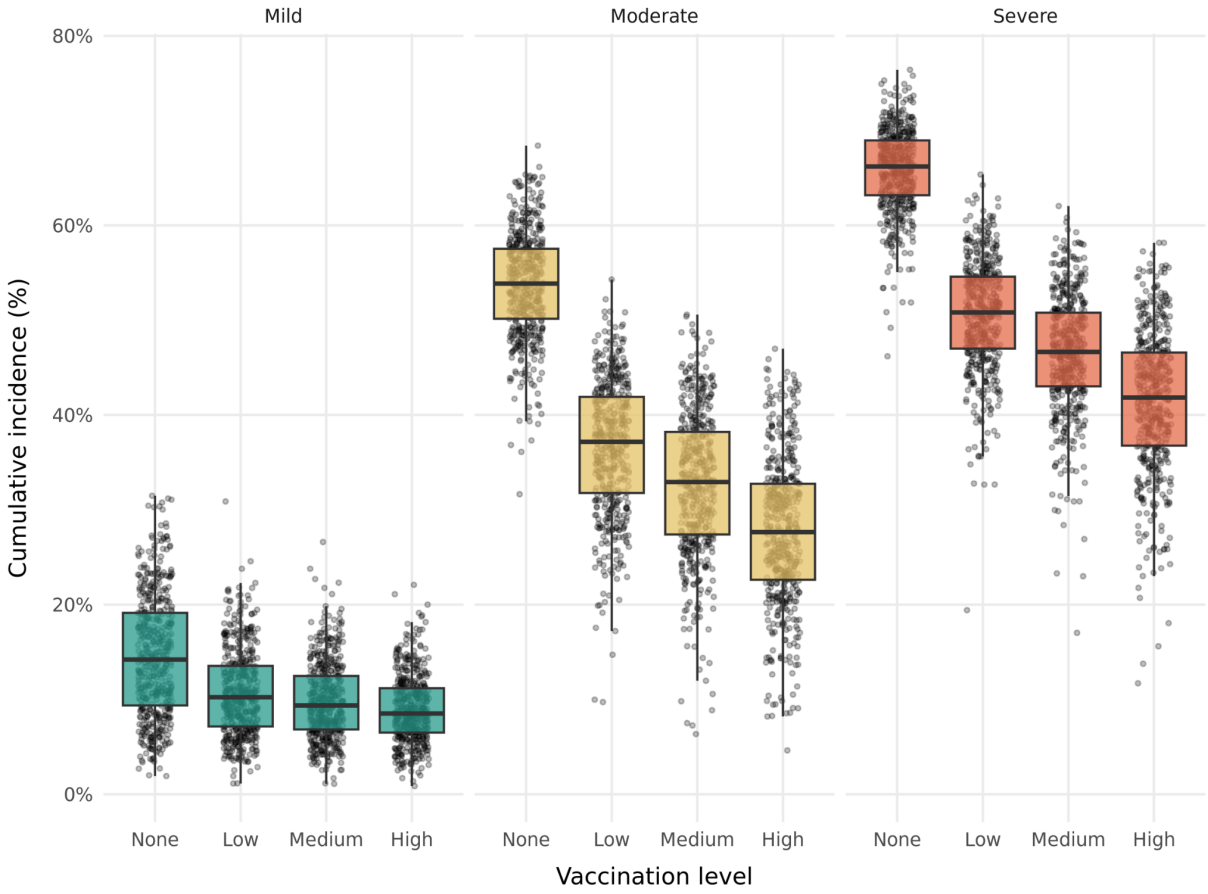


Figure 8: Cumulative incidence of influenza among faculty and staff ages 18–49 years across 500 simulations per scenario in a closed population of 1,000 agents.

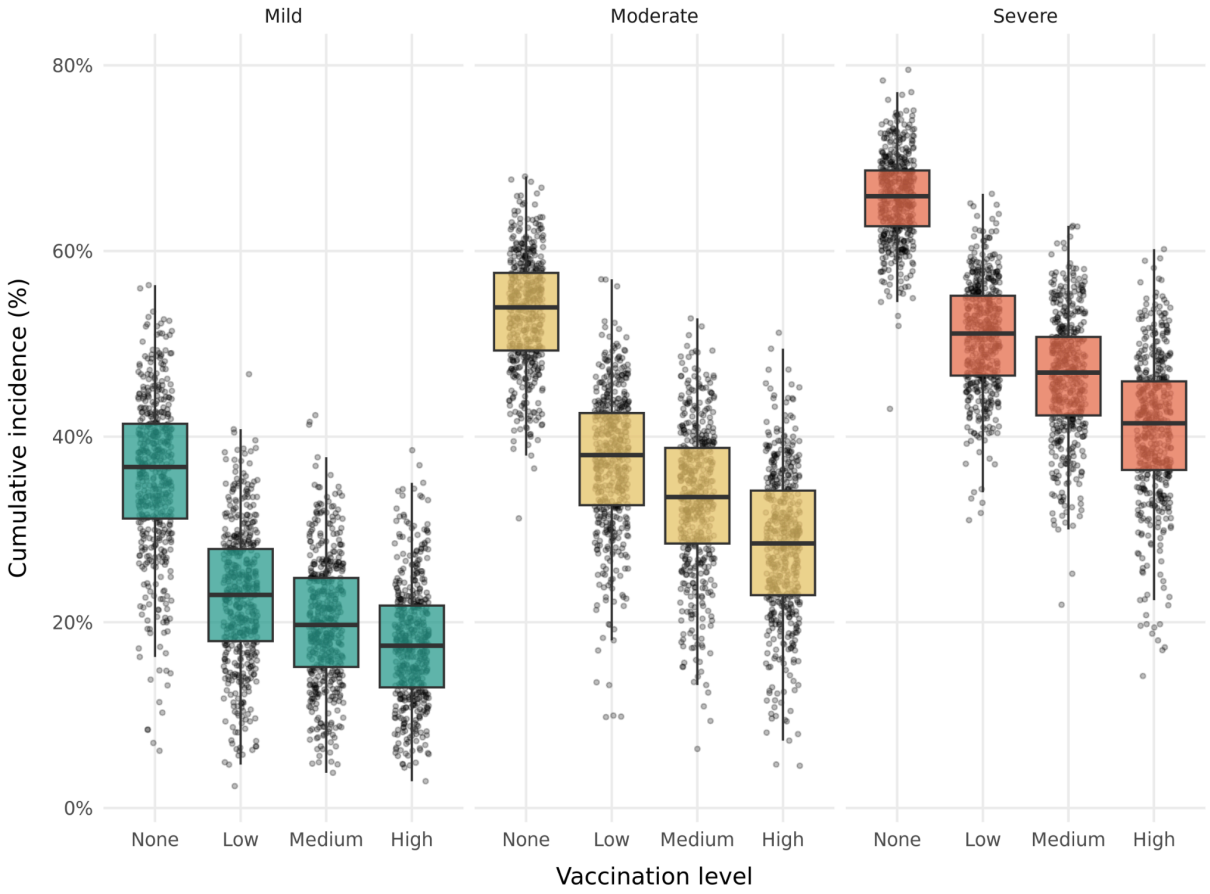


Figure 9: Cumulative incidence of influenza among faculty and staff ages 50–64 years across 500 simulations per scenario in a closed population of 1,000 agents.

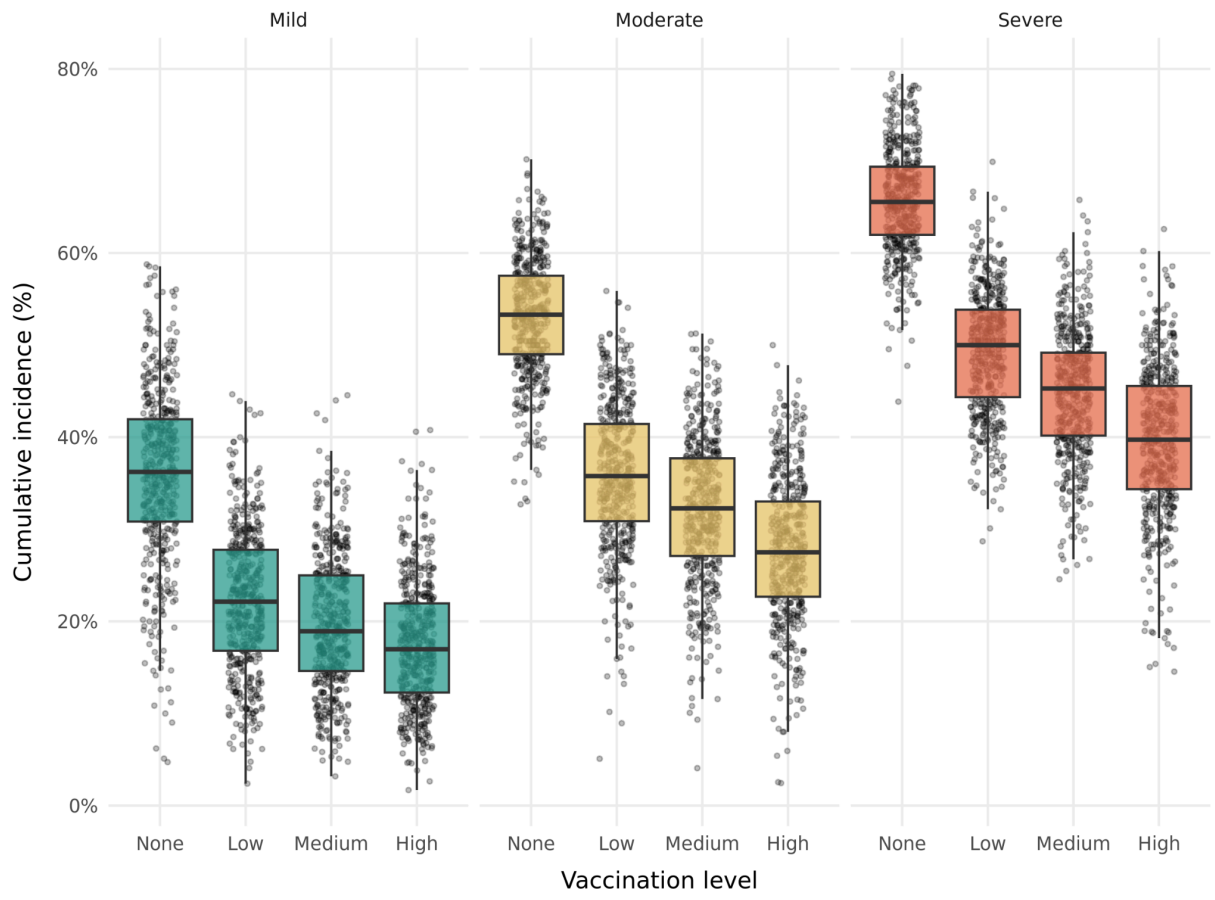
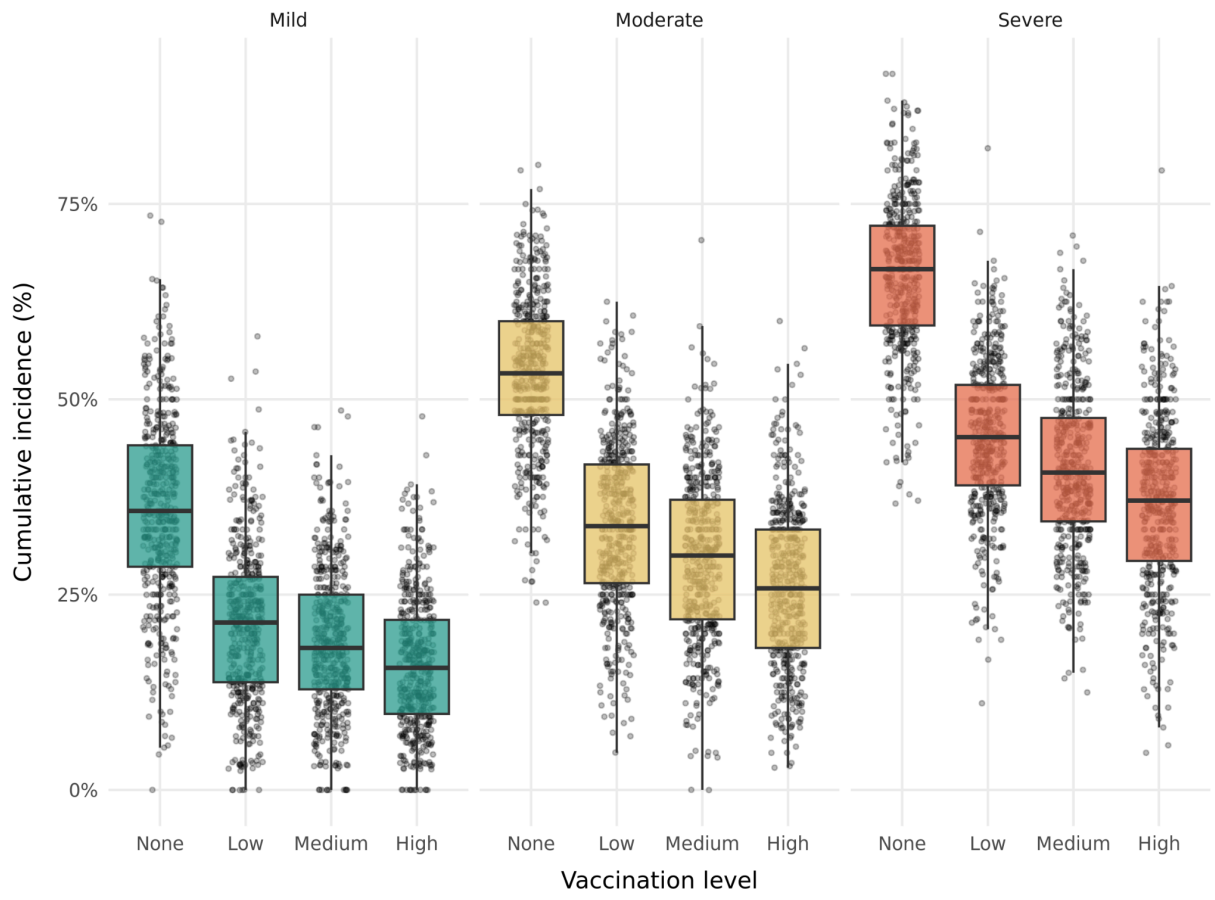


Figure 10: Cumulative incidence of influenza among faculty and staff ages 65 years and older across 500 simulations per scenario in a closed population of 1,000 agents.



Supplement

The model description partially follows the ODD (Overview, Design concepts, Details) protocol for describing individual- and agent-based models (Grimm et al., 2006), as updated by Grimm et al. (2020). The agent-based model (ABM) discussed was created using EMOD-Generic, an infectious disease modeling software developed by the Institute for Disease Modeling (IDM), an institute of the Gates Foundation (Institute for Disease Modeling, 2025b). Because some mechanisms of the EMOD software are not transparent to users, we were not able to provide the level of detail required in a complete ODD protocol (Grimm et al., 2020).

Purpose and Patterns

Purpose: The purpose of this ABM is to examine how different levels of student vaccine uptake impact the transmission of mild, moderate, and severe seasonal influenza strains in a small-scale, indoor campus setting. Like other congregate settings, college campuses frequently experience high rates of seasonal influenza transmission due to high population density and interaction between individuals (Bidari & Goldwyn, 2019; Buchsbaum et al., 2022; CDC, 2021; Chung, 2021; Eames et al., 2012; Emanuels et al., 2019; Lewis et al., 2023; M. Wang, 2017). We selected student vaccination as the independent variable of interest since uptake within this group has historically been significantly below the threshold for herd immunity, making this a potential point of intervention (Graupensperger et al., 2021; NFID, 2016, 2017; Plans-Rubió, 2012; Ryan et al., 2019; Shon et al., 2021; Skyles et al., 2024; Uddin et al., 2010). Seven agent types, distinguished by a combination of role (student, faculty, or staff) and age group (18–49 years, 50–64 years, or 65 years or older) are represented. We are interested in the extent to which altering student vaccination rates impacts the overall dynamics of the flu season and ameliorates

the burden of disease among different agent types. The effects of student vaccination uptake may vary by viral strain severity, as defined by reproduction rate and duration of the infectious period.

Patterns: Three key patterns were used as criteria to evaluate the model's suitability for this purpose. Our interest was in face validity, or the extent to which the model appears to accurately represent the real-world processes it is intended to simulate based on qualitative assessment. Quantitative calibration was not possible because empirical data on the target system (i.e., highly detailed influenza transmission data from a population of students, faculty, and staff in a small indoor setting on a university campus) were not available. First, we compared the simulated epidemic curves to those of real-world flu outbreaks in university settings. Epidemic curves documented in the literature are unimodal with a duration of approximately 50–60 days (Guh et al., 2011; Iuliano et al., 2009; Layde et al., 1980; Lewis et al., 2023; Sobal & Loveland, 1982). Second, we checked whether seasons with more severe viral strains were characterized by higher incidence (Biggerstaff et al., 2014, 2018; Budd et al., 2017; CDC, 2024a, 2024b; Jayasundara et al., 2014; Somes et al., 2018; Tokars et al., 2018). Third, we examined whether transmission was inversely related to overall vaccination rate (CDC, 2025a, 2025d; Flannery et al., 2019; Orenstein, 2018; Plans-Rubió, 2012; Rolfes et al., 2019).

Entities, State Variables, and Scales

Entities: Agents in the model represent individual people attending class or working in the building. Agents are assigned age and role attributes to roughly recreate the relevant variation in vaccination behavior in a population similar to that of the Brown University School of Public Health. Age is an important factor in vaccine uptake (KFF, 2024; Lu et al., 2021). Pairing age and role allows us to capture the unique dynamics of vaccination among college students compared to non-students in the same age group (Graupensperger et al., 2021; Ryan et al., 2019;

Shon et al., 2021). For the purpose of simplicity, all influenza spread is assumed to occur via large-particle droplets or aerosols, with no distinction drawn between the two respiratory transmission pathways (CDC, 2024a, 2025c; C. C. Wang et al., 2021). Fomite transmission, which occurs when a person touches a surface contaminated with influenza virus and then touches their mouth, nose, or eyes, is a less prevalent transmission pathway (CDC, 2024a). Therefore, we decided that the work involved in encoding fomite transmission did not outweigh the potential increase in model realism.

State variables: The agent state variables are summarized in Table 3. Age categories align with those typically used by the CDC in reporting and guidance on influenza because of clinically significant differences between younger adults (18–49 years), older adults (50–64 years), and the elderly (65 years or older) (Budd et al., 2017; Rolfes et al., 2018). The roles of student, faculty, and staff follow the designations used by Brown University (Brown University, 2023). Students, faculty, and staff vary in their distributions of age and vaccine uptake.

With regard to influenza, agents are always in one of four categories: susceptible, exposed, infected, or recovered. Susceptible agents are those who have not yet been infected and acquired immunity. An agent is probabilistically exposed when they interact with an infected agent who is contagious. After the agent's assigned incubation period elapses, the exposed agent becomes infected and is contagious—that is, able to transmit the virus to others. Once their assigned infectious period is over, the agent enters the recovered state and remains there for the duration of the simulation. An agent may be vaccinated once per season. Vaccination reduces the likelihood that someone acquires infection by 50% (CDC, 2025a; Nichol et al., 2010; Rolfes et al., 2019; Zhu et al., 2025).

Scales: The model represents time via discrete time steps. The temporal resolution, or length of each time step, is one hour. The temporal extent of the model is 212 days, or the length of time between the beginning of October and the end of April during a non-leap year, which is considered flu season in the Northern Hemisphere (CDC, 2025b).

Process Overview and Scheduling

Infection is seeded upon initialization using the *InitialPrevalence* parameter in the EMOD demographics file (Institute for Disease Modeling, 2026a). Approximately 2% of the population is randomly initialized as infected. This value was chosen because the U.S. Influenza Surveillance System uses a 2% positivity rate in its sentinel laboratory network as the threshold for elevated influenza activity (CDC, 2025e). Each agent's infectious period is determined by a random draw from a Poisson distribution with a mean of four, five, or six days, depending on strain severity (Carrat et al., 2008; WHO, 2025). Agent infectivity in each scenario is set using the *Base_Infectivity* parameters in the EMOD configuration file. Infectivity equals the basic reproduction number (R_0) divided by the mean infectious period. R_0 is the expected number of secondary cases resulting from a single primary case in a fully susceptible population (Institute for Disease Modeling, 2026b). Non-infected agents start in a susceptible state. Agents' SEIR state variables are set to "Infected" or "Susceptible" accordingly.

Agents interact randomly in the model, with flu transmission potentially occurring when an infected and a susceptible agent come into close contact. "Susceptible"-state agents randomly selected as contacts have their SEIR state changed to "Exposed" and are assigned an incubation period based on a random draw from a Poisson distribution with a mean of two days (Carrat et al., 2008; Lessler et al., 2009; WHO, 2025). If an agent is already in an exposed, infected, or recovered state, then no action results from their contact with the contagious person. SEIR state

variables are updated every hour. Once an agent's incubation period elapses, their state is changed to "Infected." Once an agent's infectious period elapses, their state is changed to "Recovered." The recovery rate is the reciprocal of the average duration of illness (Institute for Disease Modeling, 2025a).

The *Symptomatic_Infectious_Offset* parameter in the EMOD configuration file is set to one day, meaning agents are contagious for 24 hours before they show symptoms (Carrat et al., 2008; Institute for Disease Modeling, 2026b; WHO, 2025). This coding of symptomaticity offers a future avenue for extending the model such that agents can accurately sense when they are ill and change their behavior in response. It is plausible to assume people can generally infer they have the flu based on the appearance of upper respiratory infection symptoms accompanied by fever or body aches (NFID, n.d.). Rapid antigen detection and molecular assay tests are commonly used to diagnose flu in clinical settings (Cleveland Clinic, 2025), and relatively accurate home antigen tests are now commercially available as well (FDA, 2024; Geyer et al., 2022). SEIR state sensing would enable the model to include adaptive, risk-reducing behaviors, wearing a face mask or seeking vaccination, based on an agent's own disease state or the observation of disease in their network.

The first of eight weekly flu vaccine distributions, implemented using an intervention event in the EMOD campaign file (Institute for Disease Modeling, 2026c), takes place at time 0. Vaccines are offered early in the season, as is real-world public health practice (CDC, 2024c; Nichol et al., 2010). Vaccine eligibility is restricted to unvaccinated agents. Faculty and staff vaccine uptake is constant by age group across vaccination scenarios, while student vaccine uptake varies. A specified proportion of the unvaccinated population is randomly selected for vaccination at each distribution. Because the population of eligible agents shrinks with each

distribution, the number of agents vaccinated decreases over time. Additionally, small population size, particularly of faculty and staff, introduces considerable variation in overall coverage. The target rates for faculty and staff are based on vaccine uptake among adults in Rhode Island: 46.8% among those 18–49 years old, 59.6% among those 50–64 years old, and 79.5% among those 65 or more years old (KFF, 2024). The per-vaccine-distribution demographic coverage was calculated for each AgeRole as follows:

$$Demographic\ coverage\ =\ 1-(1-target\_rate)^{\frac{1}{8}}$$

Weekly demographic coverage probabilities are provided in Table 4. Under low student uptake, the seasonal target rate for students is 23.4%, half that of non-students ages 18–49 years. Under medium student uptake, the seasonal target rate for students is 46.8%, equal to that of non-students ages 18–49 years, requiring a 7.6% weekly demographic coverage probability. Under high student uptake, the seasonal target rate is 70.2%, 1.5 times that of non-students ages 18–49 years.

Design Concepts

Basic principles: Influenza (flu) is an infectious respiratory disease caused by influenza viruses A, B, C, and D. Influenza A and influenza B are the agents responsible for annual influenza epidemics (seasonal flu), which typically peak between December and February in the United States (CDC, 2025b). The full flu season lasts from the beginning of October through the end of April in the Northern Hemisphere (CDC, 2024a). Flu is transmitted person-to-person via large-particle droplets or aerosols (Ijaz et al., 2025). Fomite transmission via contaminated surfaces is another possible pathway, though less prevalent (CDC, 2024a). The virus can cause mild to severe illness depending on the individual and the virus strain (CDC, 2025b). Symptoms

include fever, cough, sore throat, body aches and fatigue and typically last around one week (Carrat et al., 2008; WHO, 2025). It is estimated that 3-11% of the US population contracts the flu each year (Tokars et al., 2018). In high severity flu seasons, such as 2014-2015 and 2017-2018 (CDC, 2024e), influenza can be associated with more than 1 million hospitalizations and 50,000 to 100,000 deaths in the United States (CDC, 2019a, 2023; Elflein, 2025). Adults over 65 years of age are at greatest risk of influenza-related hospitalization and death. Other groups prone to more serious illness include children under 5 years old, pregnant people, and those with chronic medical conditions (WHO, 2025).

Like other congregate settings, college/university campuses frequently experience high rates of flu transmission (Bidari & Goldwyn, 2019; Buchsbaum et al., 2022; Emanuels et al., 2019; Nichol et al., 2006). The fact that campus outbreaks are often not mirrored in community settings suggests something distinct about influenza transmission on college campuses (Lewis et al., 2023). The epidemic spread of acute respiratory infections on campuses is primarily a function of high population density and interaction between individuals (Buchsbaum et al., 2022; NFID, 2016; M. Wang, 2017). Additionally, students tend to get less rest, have poorer nutrition, and consume more alcohol than the general population (Strelnikova, 2023). These habits, combined with the stress of navigating a new, often demanding environment, reduce the body's ability to fight infection, driving transmission (Barrett, 2023). Critically, influenza vaccination uptake among college students has historically been well below the coverage threshold for herd immunity, which would be about 75% when $R_0 = 1.6$ and vaccine effectiveness is 50% (NFID, 2016; Orenstein, 2018). Just 43% of the 20,623 students surveyed in the Fall 2025 National College Health Assessment (NCHA) reported receiving a flu vaccine in the preceding twelve

months (ACHA, 2026). This is the continuation of an overall downward trend in flu vaccination since Fall 2020 (Figure 1).

We are interested in how different levels of student vaccine uptake impact transmission in an indoor setting where people of different ages and roles interact on a daily basis. It is estimated that humans spend about 90% of their time indoors (Horve et al., 2020). Indoor environments are where the vast majority of close-contact interactions take place, and poor ventilation indoors as compared to outdoors means we are more likely to experience sustained exposure to infectious doses of respiratory pathogens like influenza (Barron, 2023). Given that students make up the majority of the campus population and exhibit the highest rates of social mixing on average (Ibuka et al., 2016; Kwok et al., 2014; Leung et al., 2017; Y. Liu et al., 2020; Zivich et al., 2020), their vaccination behavior has a large impact on outbreak dynamics. High vaccination rates among students could significantly reduce the overall transmission risk by lowering the incidence of influenza across the campus community, reducing the chances that faculty and staff, who tend to be older and at higher risk for adverse outcomes, acquire infection.

The model represents influenza as an SEIR-type pathogen. Individuals occupy one of four states in relation to the virus: susceptible, exposed, infected, or recovered. All agents start the simulation as susceptible, representing the general state of immunity at the start of each flu season due to antigenic shift (Krammer et al., 2018). Interactions with infectious potential result in susceptible agents becoming exposed. The exposed agent advances through the infected state to recovery. The rate at which agents move from exposed to infected is the incubation rate (Institute for Disease Modeling, 2025a), on average two days. The infectious period is assumed to begin when an agent transitions from exposed to infected, with symptomaticity lagged by one day (Carrat et al., 2008; CDC, 2025b; Lessler et al., 2009; WHO, 2025). This offset between

contagiousness and symptomaticity creates the potential for asymptomatic transmission. Agents do not reenter a susceptible state after recovery, as would occur with an SEIRS-type pathogen, since only one virus strain is in circulation during the season modeled and within-season reinfection is exceedingly rare (CDC, 2024b).

The implicit motivation of each agent is to avoid illness. Agents may receive a flu vaccine to reduce their risk of infection. Seasonal flu vaccines are developed, based on surveillance of viral activity and predictive models, to target the most common influenza viruses of the year (CDC, 2024c). Individuals who are vaccinated against seasonal influenza are less likely to become infected following exposure (CDC, 2025a, 2025d) and experience shorter durations of illness on average (Carrat et al., 2008; Ferdinands et al., 2021; Nichol et al., 2010). Vaccine effectiveness at preventing infection is standardized at 50% based on studies by the CDC and independent research teams of the past 20 flu seasons (CDC, 2025d). In accordance with studies on flu vaccination, uptake is positively associated with age (KFF, 2024; Lu et al., 2021).

Emergence: Since the simple version of the model does not incorporate adaptation, there are no emergent results driven by agent behavior. Rather, the shape, scale, and duration of the simulated epidemics arise from the stochasticity encoded in agent interactions, disease transmission, vaccine uptake according to age and role, and selection to receive the vaccination intervention.

Adaptation: A potential extension of the model to include adaptation based on SEIR state sensing is described in the process overview above.

Objectives: Each agent's implicit objective is to avoid becoming infected. Extensions of the model that include both acquisition- and transmission-blocking interventions (e.g., masking) could incorporate a second objective of not infecting others.

Learning: Learning is not implemented.

Prediction: Prediction for adaptive behavior is not represented in the model.

Sensing: A potential extension of the model to include SEIR state sensing is described in the process overview above.

Interaction: The agents an infected agent interacts with are randomly selected and assumed to be those in close physical proximity to the infected agent (CDC, 2024a).

Stochasticity: The process of exposing other agents to infection, acquiring and recovering from infection, and deciding to be vaccinated are modeled as stochastic. Random agent mixing and stochasticity in infectivity are intended to represent random chance in real-world contact networks and capture the uncertainty of influenza virus transmission, especially since fomite transmission is not explicitly modeled. Stochasticity in the duration of the incubation and infectious periods attempts to capture variability in disease course without modeling the causes of that variability at the level of individual immune response. Stochasticity in vaccine uptake represents uncertainties about the cognitive, psychological, and social reasons people do or do not receive flu vaccinations.

Collectives: The model includes no collectives.

Observation: No virtual scientist or other special techniques are used to improve comparison of model results to empirical observations. The key model outputs used for analyses are: the number of new infections, used to calculate cumulative incidence; the first time step at which transmission is zero and there are no "Exposed" or "Infected" agents, used to calculate the

outbreak duration; and the number of "Infected" agents, used to calculate peak prevalence. These data are derived from the default output file (InsetChart.json) EMOD produces for each simulation run and from the property-based output file (PropertyOutput.json) generated by setting *Enable_Property_Output* equal to 1 in the configuration file (Institute for Disease Modeling, 2026d). Stratification is employed to compare outcomes across age group, role, and vaccination status.

Initialization

Upon initialization, 1,000 agents are created with the following distribution of age and role: 65.0% students ages 18–49 years, 5.9% faculty ages 18–49 years, 14.9% staff ages 18–49 years, 3.9% faculty ages 50–64 years, 7.2% staff ages 50–64 years, 1.2% faculty ages 65 years and older, and 1.9% staff ages 65 years and older. Agents are assigned age and role attributes to roughly recreate relevant variation in vaccination behavior. Infection is always seeded at time 0 using the *InitialPrevalence* parameter. Approximately 2% of the population is randomly selected to start in an infected state. All other agents start as susceptible and unvaccinated, representing the general state of immunity at the start of each flu season due to antigenic drift (CDC, 2024b).

Twelve outbreak scenarios, each based on a combination of flu strain severity and student vaccination rate (Table 1), are simulated in 500 model runs per scenario. Different basic reproduction rates and mean infectious periods are used in the EMOD configuration file to characterize mild, moderate, and severe viral strains. The rate of student vaccination is modeled as 50%, 100%, and 150% the rate of vaccination among faculty and staff ages 18–49 years. Vaccination rates are specified in the EMOD campaign file (Institute for Disease Modeling, 2026c).

Input Data

The model does not use any input data to represent variables that change over time or events that occur during a simulation.

Submodels

Demographics: Demographics are dictated by parameters set in the EMOD demographics file. The age categories in the model align with those typically used by the CDC in relation to influenza because of clinically significant differences between younger adults ages 18–49 years, older adults ages 50–64 years, and the elderly ages 65 years or older (Budd et al., 2017; Rolfes et al., 2018). The marginal distribution of roles (65% students, 11% faculty, and 24% staff) is based on statistics published by the Brown University Office of Institutional Research (Brown University, 2023, 2025b). In accordance with that same Brown University data, all students are assumed to be younger adults (2025b). Based on literature about the academic workforce, 54% of faculty are assigned to the younger adult age group, 35% to the older adult age group, and 11% to the elderly age group (McChesney & Bichsel, 2020; TIAA Institute, 2018). Based on data about higher education employees from the U.S. Bureau of Labor Statistics, 62% of staff are assigned to the younger adult age group, 30% to the older adult age group, and 8% to the elderly age group (2025). The joint AgeRole distribution is calculated based on the marginal and conditional probabilities (Table 2) as follows:

$$Pr(Age_i, Role_j) = Pr(Age_i \mid Role_j) \times Pr(Role_j)$$

- $i = \{Younger\ adult,\ Older\ adult,\ Elderly\}$
- $j = \{Student,\ Faculty,\ Staff\}$

Of the 1,000 agents in the model, 65.0% are students ages 18–49 years, 5.9% are faculty ages 18–49 years, 14.9% are staff ages 18–49 years, 3.9% are faculty ages 50–64 years, 7.2% are staff ages 50–64 years, 1.2% are faculty ages 65 years and older, and 1.9% are staff ages 65 years and older.

Infection: Disease dynamics are dictated by parameters set in the EMOD configuration file. The incubation period distribution and symptomatic-infectious offset are the same across all twelve outbreak scenarios. Each exposed agent's incubation period is randomly drawn from a Poisson distribution with a mean of two days. This timeline aligns with World Health Organization guidance and systematic reviews of disease course studies, which suggest the incubation period is two days on average but can be anywhere from one to four days depending on the individual (Carrat et al., 2008; Lessler et al., 2009; WHO, 2025). The *Symptomatic_Infectious_Offset* parameter is set to one day, meaning agents are contagious for 24 hours before they show symptoms (Carrat et al., 2008; WHO, 2025).

Different infectious period and base infectivity distributions characterize the mild, moderate, and severe strain scenarios. An agent's infectious period is the timeframe during which they can transmit disease to others. The population distribution of influenza infectious periods follows a Poisson distribution, as illustrated by Carrat et al.'s review of volunteer challenge studies (2008). *Base_Infectivity* is the average number of individuals per day who will be exposed to infection by one infectious individual. Infectivity equals the basic reproduction number (R_0) divided by the mean infectious period, where R_0 is the expected number of secondary cases resulting from a single primary case in a fully susceptible population (Institute for Disease Modeling, 2026b). Symptoms deterministically appear one day after the infectious period begins (Carrat et al., 2008; WHO, 2025). In the mild strain scenario, R_0 is set to 1.2,

around the 25th percentile of seasonal influenza reproduction numbers calculated in a systematic review by Biggerstaff et al. (2014). The mean infectious period is set to four days, the average for influenza B in Carrat et al.'s review (2008). In the moderate strain scenario, R_0 is set to 1.4, around the 75th percentile of seasonal influenza reproduction numbers calculated by Biggerstaff et al. (2014). The mean infectious period is set to five days, the average for influenza A/H1N1 in Carrat et al.'s review (2008). In the severe strain scenario, R_0 is set to 1.6. This R_0 value is in the fourth quartile of reproduction numbers for seasonal influenza (Biggerstaff et al., 2014). The mean infectious period is set to six days, which is frequently cited as on the high end of illness duration (CDC, 2025b; WHO, 2025).

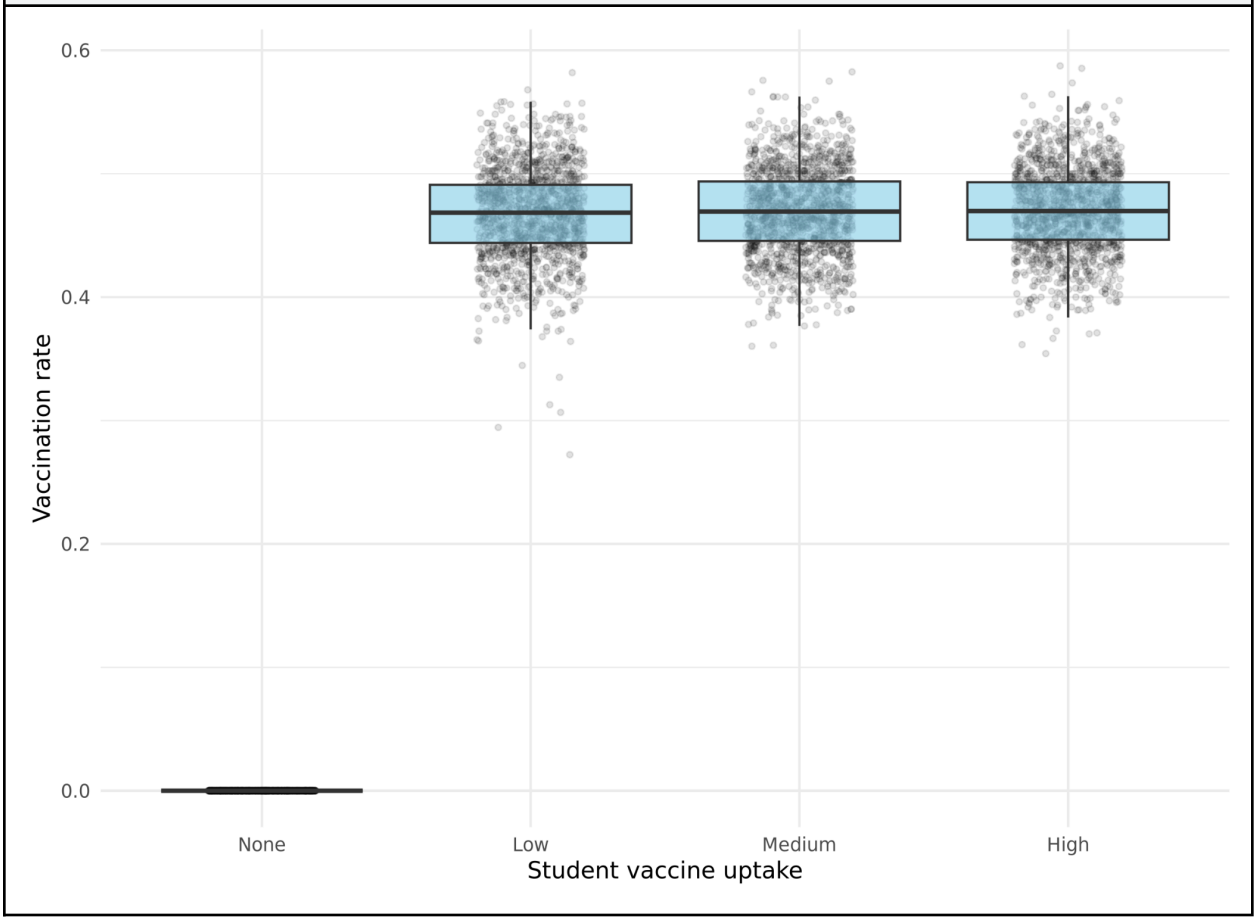
Vaccination: Vaccination is coded as a series of distributions in the EMOD campaign file. In this model, vaccines are dispensed eight times, beginning at time 0, with 168 hours (seven days) between distributions. Each AgeRole demographic is targeted (using *Property_Restrictions*) with its own vaccine intervention to calibrate subgroup uptake. Vaccination is administered by the *StandardInterventionDistributionEventCoordinator* class, which can distribute an individual- or node-level intervention to a specified fraction of entities set with the *Demographic_Coverage* parameter (Institute for Disease Modeling, 2026e). The *MultiInterventionDistributor* is used to simultaneously apply "Vaccine" and "PropertyValueChanger" interventions to the randomly selected agents. The former intervention reduces an agent's infection acquisition risk by 50%. Vaccination is modeled as providing full effects in every recipient, and effectiveness does not wane over time. The latter intervention updates the agent's *InterventionStatus* property from unvaccinated to vaccinated. The *InterventionStatus* property is important because it allows tracking of how many agents are

vaccinated and is used to prevent individuals from receiving multiple vaccinations in a single season (Institute for Disease Modeling, 2026c).

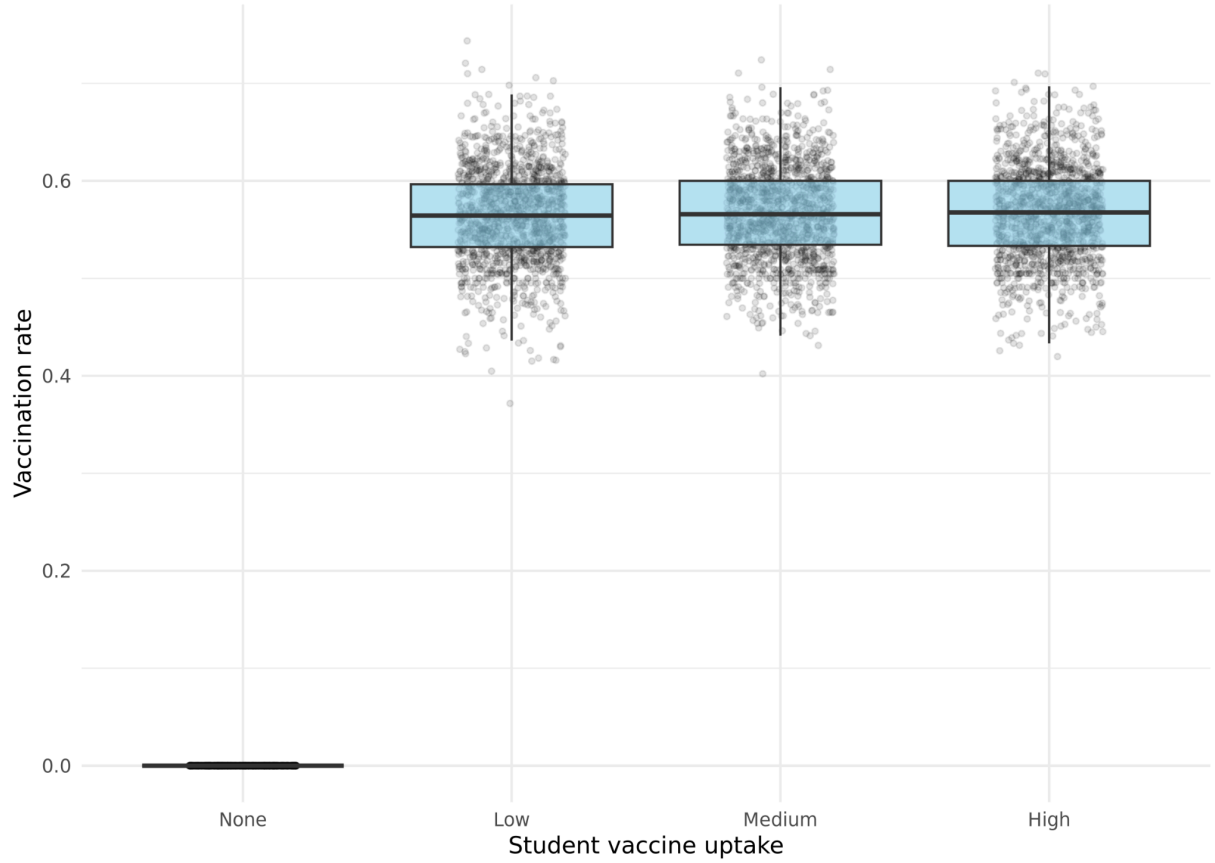
Faculty and staff vaccine uptake is constant by age group across scenarios, while student vaccine uptake varies. The target rates for faculty and staff are based on vaccine uptake among adults in Rhode Island: 46.8% among those 18–49 years old, 59.6% among those 50–64 years old, and 79.5% among those 65 or more years old (KFF, 2024). (See above for details on the calculation of the *Demographic_Coverage* parameter). Non-student vaccination rates satisfactorily approximated the targets set (Supplementary Figure 1, Supplementary Figure 2, Supplementary Figure 3).

The effects of altering student vaccination rates are explored by setting uptake to be lower, higher, and equal to that of faculty and staff in the younger adult age group. In the low student vaccine uptake scenario, the target vaccine uptake rate is 23.4%, half (0.5 times) that of faculty and staff ages 18–49 years. The weekly demographic coverage for students in the low uptake scenario is 3.3%. In the medium student vaccine uptake scenario, the target vaccine uptake rate is 46.8%, equal to that of faculty and staff ages 18–49 years. The weekly demographic coverage for students in the medium uptake scenario is 7.6%. In the high student uptake scenario, the target vaccine uptake rate is 70.2%, 1.5 times that of faculty and staff ages 18–49 years. The weekly demographic coverage for students in the high uptake scenario is 14%. Non-student vaccination rates satisfactorily approximated the targets set (Supplementary Figure 4).

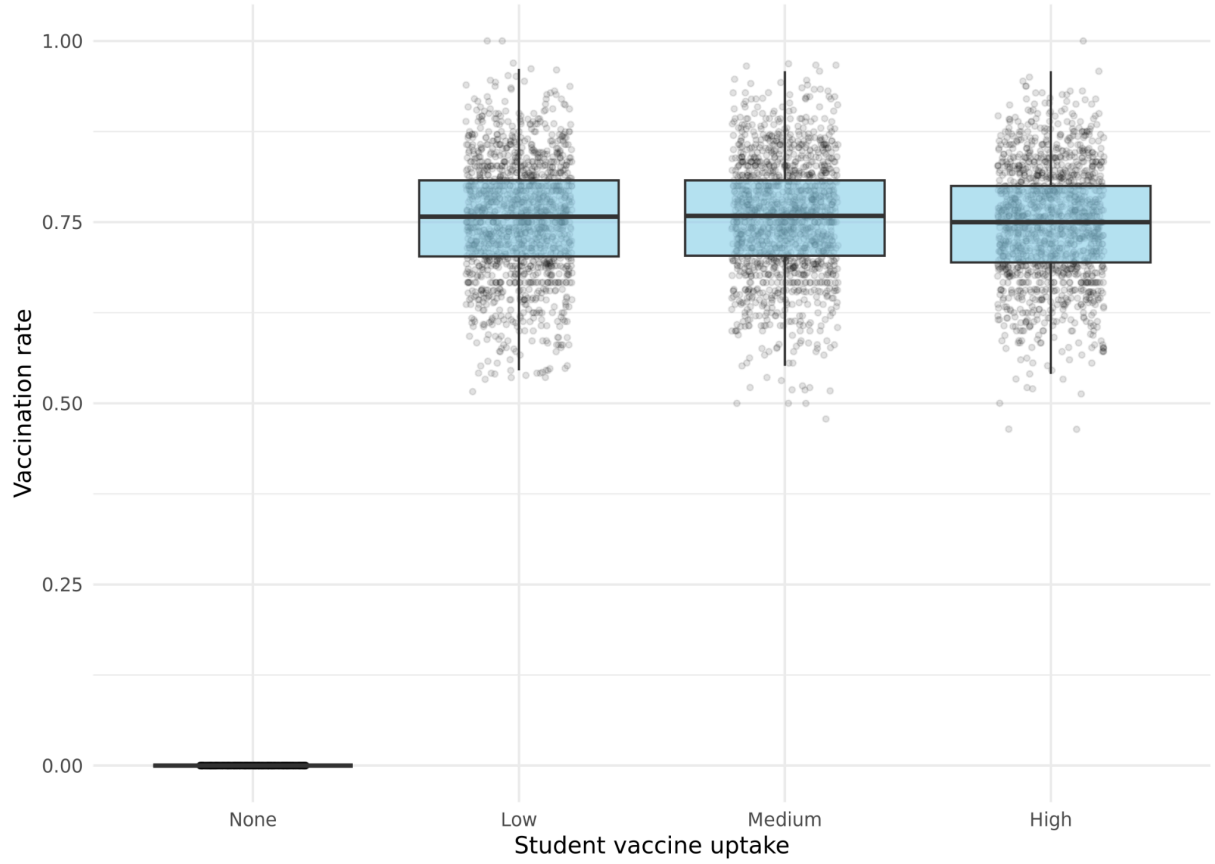
Supplemental Figure 1: Distribution of vaccination rates among faculty and staff ages 18–49 years from simulated influenza seasons (500 per scenario) in a closed population of 1,000 agents, approximately 20.8% of whom are in the non-student ages 18–49 subpopulation. Target rates by scenario are: 0.0% under no vaccination and 46.8% under low, medium, and high student vaccination.



Supplemental Figure 2: Distribution of vaccination rates among faculty and staff ages 50–64 years from simulated influenza seasons (500 per scenario) in a closed population of 1,000 agents, approximately 11.1% of whom are in the non-student aged 50–64 subpopulation. Target rates by scenario are: 0.0% under no vaccination and 59.6% under low, medium, and high student vaccination.



Supplemental Figure 3: Distribution of vaccination rates among faculty and staff ages 65 years and older from simulated influenza seasons (500 per scenario) in a closed population of 1,000 agents, approximately 3.1% of whom are in the non-student aged ≥ 65 subpopulation. Target rates by scenario are: 0.0% under no vaccination and 79.5% under low, medium, and high student vaccination.



Supplemental Figure 4: Distribution of vaccination rates among students from simulated influenza seasons (500 per scenario) in a closed population of 1,000 agents, approximately 65% of whom are students. Target rates by scenario are: 0.0% under no vaccination, 23.4% under low vaccination, 46.8% under medium vaccination, and 70.2% under high vaccination.