The Implementation of Awareness Into Epidemiological Models

Austin Carlin, Tomasz Frelek

Abstract

With modeling disease spread in epidemiology being a major area of research, this paper utilized an already proposed model that integrates awareness into its system to simulate deaths over time for COVID-19, and applied it to two similar disease scenarios for hospitalizations, H1N1 and a standard seasonal flu, that had drastically different awareness and reactions from society. This model was found from a paper by Weitz et al., and their system was applied to Python from MATLAB code. The standard seasonal flu has a yearly occurrence that most individuals and families are knowledgeable of, while H1N1, or Swine Flu, was a novel strain of the influenza A virus that was greatly incorporated into the media and instigated a worldwide pandemic. For these models, the parameters were determined both from Weitz et al.'s research, as well as general research, to generate a prediction that was compared and altered to best fit data of deaths or hospitalizations in a given time period for each specific disease. The models produced indicated that the system is accurate in providing a model for the first outbreak from data of a given disease, as well as other features, but the model is unable to predict larger secondary outbreaks that result from extraneous factors. From the implementation of this model for various diseases, it is clear that awareness is an important factor in disease spread that should be taken into account in future epidemiological models.

Introduction

Since the inception of epidemiology, disease models have been utilized in predicting and representing the progression of disease through time. They are integral to the visualization of the spread of specific diseases and can also be used to ascertain the influence of various factors in affecting the disease as a whole. One disease that has gained a great amount of interest in recent years in COVID-19. COVID-19 is a disease that is caused by the SARS-CoV-2 virus. It is able to spread quickly and can induce complications with the respiratory system of those infected [1]. In the United States, there have been over 100 million cases and 1 million deaths of this disease since its outbreak in the country [2].

Another disease that has had a significant impact on the United States throughout the years is influenza (flu), which is also a respiratory disease and is contracted due to the influenza virus. The symptoms of this disease include a sore throat, cough, and fever[3]. This disease, in about the last decade, has been responsible for 10-40 million cases and 5-50,000 deaths annually in the United States[4]. The flu does differ from COVID-19 in the fact that it has been prominent for many more years and has a "yearly season," meaning it is a disease that society has been conscious of year after year. Among the plethora of yearly flu strains, there was one strain that caused much more distress than normal around the 2009 season, called H1N1, popularly known as Swine Flu. H1N1 was a novel influenza A virus that became widespread because it was a new strain of the influenza virus that people had little to no immunity against, and it spread globally at an alarming rate which instigated a worldwide pandemic [5]. Due to the H1N1 virus being considered a pandemic, the world was more alert about the disease. It especially raised concern in the United States when the H1N1 disease was branded a Public Health Emergency of International Concern. Shortly after, the World Health Organization (WHO), increased the level of the pandemic from a phase 3 to a phase 4, and again to a phase 5 pandemic.

When modeling a disease, most models take into account epidemiological information such as transmission rate, latent period, infectious period, etc. However, a population's awareness of a disease is an often forgotten metric that can have great effect on the overall spread of the disease because it alters how individuals react in presence of the disease. For example, in the case of H1N1, it was found that children under the age of 5 and pregnant women were at a higher risk of more serious complications if they contracted the disease [7]. This increased risk to youth prompted the closing of many schools in high-risk areas to minimize the spread and impact of the disease [6]. Being conscious of information like this may change how a society reacts to the spread of a disease, and it is important to factor this into disease simulations to create a more accurate model.

This paper will dive into a specific disease model, developed by Joshua S. Weitz et al., that expands on the factors of awareness when modeling the progression of a disease [8]. Specifically, this paper proposed a methodology for accounting for population awareness in disease simulations by taking into account a population's short and long-term awareness of death. Using this model, Weitz was able to accurately model the infections and deaths per day of COVID-19 with different awareness-based methods with fatalities and mobility of the individuals in a given population. Given this model and its applications for the COVID-19 pandemic, we implemented it for both H1N1, and for a normal flu season (2013-2014) to ascertain whether the method for modeling awareness proposed by Weitz et al. holds for applications to other diseases.

Methods

In order to accurately model these diseases, while taking into account various parameters, such as short-term awareness and long-term awareness of deaths, a dynamical set of equations needed to be outlined. As discussed previously, Weitz et al. proposed a model that explored the effects of multiple parameters on how awareness can alter the spread of COVID-19. We wanted to determine if their proposed model could be altered and applied to different diseases, like seasonal flu and H1N1, to ultimately determine if population awareness factors could be a useful tool in accurately modeling diseases

The model used in this paper is derived from the model proposed by Weitz et al. In their research, they suggested an altered SEIR model that took into account hospitalization, deaths, and short and long term awareness of individuals in the population. Since the work in this paper is focused on seasonal influenza and H1N1, research was conducted to determine the parameters for these diseases that were utilized in Weitz et al.'s final model. Weitz et al.'s extended SEIR model, can be described by the equations below [8]:

$$\dot{S} = -\frac{\beta SI}{[1+(\delta/\delta_c)^k + (D/D_c)^k]} \tag{1}$$

$$\dot{E} = \frac{\beta SI}{[1+(\delta/\delta_c)^k + (D/D_c)^k]} - \mu E \tag{2}$$

$$\dot{I} = \mu E - \gamma I \tag{3}$$

$$\dot{R} = (1 - f_D)\gamma I \tag{4}$$

$$\dot{H} = f_D \gamma I - \gamma_H H \tag{5}$$

$$\dot{D} = \gamma_H H \tag{6}$$

The equations in this model follow multiple compartments. These are susceptible (S), exposed (E), infected (I), recovered (R), hospitalized (H), and dead (D). For these compartments, there are many different parameters that need to be determined in order to have sufficient information to follow through with the model. These parameters include transmission rate (β), the rate at which infected individuals transmit the disease to susceptible individuals; latent period ($\frac{1}{\mu}$), the time it takes for an individual to develop symptoms following transmission; infectious period ($\frac{1}{\gamma}$), the total time that an individual is infected; the time spent in a hospital prior to death ($\frac{1}{\gamma_H}$); infection fatality probability (f_D), the chances that an individual with the disease will pass away; total population size (N); half-saturation constant for short term awareness (δ_c), the limit of how much increase in daily death the population can take; half-saturation constant for long-term awareness (D_c), the measure of total deaths the population considers; and sharpness of change in the force of infection (k) [8]. In this context, the half-saturation constant for short-term awareness represents the number of recent deaths (daily or weekly) that a population is willing to endure before taking preventative measures, and the half-saturation constant for long-term awareness represents the amount of total deaths (since the beginning of the outbreak) that a population is willing to endure before taking preventative measures. It should be noted that the awareness parameters are in respect to total population size; since we use a population size of 30e7 in this paper, these values will be very small. It should also be noted that the scale of the awareness parameters is inversely proportional to the population's "awareness" of the disease. This means that lower parameter values correspond to a higher sense of awareness(as the population has a lower threshold of death) and will lead to less infections/deaths and vice versa. Finally, k is meant to represent how quickly a population reacts to short and long-term deaths.

Conceptually, the justification for the awareness parameters is that as a population accumulates short-term and long-term deaths, they will begin taking action to protect themselves and to prevent the spread of disease.

Once the equations used in the simulations were established, they were implemented in code. Weitz et al. completed all of their simulations in MATLAB and provided their MATLAB code in their GitHub [10]. However, we found their code to be obtuse and not well documented, so we decided to recreate their model for ease of use and to better modify it for our needs. In their paper, Weitz et al thoroughly outlined the parameters and implementation for their model, so, using their code as a baseline, we recreated their model in Python.

Once the equations were set in Python, the model was first checked using the parameters that Weitz used in their simulation based on COVID-19 to ensure its viability and matching of the graphs Weitz developed. From the paper by Weitz et al., and the GitHub files of code and outputs they provided, the parameter values for the COVID-19 based model were determined. The data for COVID-19 deaths was found from a COVID-19 tracking website, and was based on the deaths per day up until March 7, 2021 [9]. The epidemiological parameters were kept the same as those used by Weitz et al.; however, since Weitz et al. never directly implemented their model on the COVID-19 data, we had to experimentally determine the values of the short-term awareness and long-term awareness parameters. Additionally, the total population was changed to 30e7 (Weitz et al used 10+e7 for testing purposes). The remaining parameters were the same as in the Weitz et al. paper [8]. The final values of these parameters following modification are shown:

Table 1: Parameter values for COVID-19 model

Description	Parameter	Value
Transmission rate	β	0.5 days^{-1}
Latent period	$\frac{1}{\mu}$	2 days
Infectious period	$\frac{1}{\gamma}$	6 days
Hospitalization period	$\frac{1}{\gamma_H}$	27 days
Fatality probability	f_D	0.01
Total population	N	30*10e7 people
Half saturation constant for short-term awareness	δ_c	25e-7 deaths/day per N

Half saturation constant for long-term awareness	D_c	4000e-7 deaths per N
Sharpness of change in force of infection	k	2

After applying Weitz et al.'s model to COVID-19, we applied it to other diseases. To test the impact of awareness on model accuracy, it was important to choose a disease where behavior could change with awareness. The 2013-2014 seasonal flu and H1N1 were selected because they represent two sides of the same coin. Both are flu outbreaks, but H1N1 was classified as a pandemic and received vast media attention, whereas the 2013-2014 flu was treated as any other normal flu season. Additionally, the primary strain in the flu outbreak in 2013-2014 was actually a weaker strain of H1N1 [18], meaning that the two outbreaks were extremely similar epidemiologically. This allowed us to use the same epidemiological parameters for both disease models which means that the main difference between the two models would be due to the awareness parameters, which helped isolate and emphasize the impact of awareness.

We were curious whether the difference in public attention and media sensationalization between H1N1 and the standard flu would be represented accurately in Weitz et al.'s model. Since people were more aware of H1N1, the model representing infection curve for H1N1 should have much lower awareness parameters than those of the model for the 2013-2014 flu. Since people were more aware and fearful of H1N1 they would be more eager to protect themselves from it than a normal flu that was never sensationalized (despite the fact that the two diseases are actually very similar).

While the COVID-19 implementation of the model was based directly on Weitz et al.'s implementation, we slightly modified the model in order to apply it to H1N1 and the seasonal flu. f_D was changed to f_H - from fatality probability to hospitalization probability - as the fatality probability of both H1N1 and the seasonal flu is so low (about 0.0002) [19] that there was not a statistically significant number of deaths from either disease in the data that we used. In doing this, the compartment of the model involving deaths was also altered to now track recovery from the disease following hospitalization. There were, in contrast, a sizable number of hospitalizations due to both diseases. By altering the model in this way, the population's awareness was now based on the number of hospitalizations, instead of the number of deaths. However, this substitution is justified as the number of hospitalizations still serves as an effective proxy for how aware a population is for a disease, as hospitalization is still a scary prospect that would motivate people to take precautions against a disease.

Research was conducted to find the necessary parameter values for H1N1 and the 2013-2014 seasonal flu. It was decided that the model would simulate the effect of these diseases in the United States. For both seasonal flu and H1N1, the values were found from articles with different sizes of scope, but only the values that would make the most sense in having the ability to be generalized for the entire United States, such as death rate, latent period, etc. Otherwise, the parameter values found were in respect to the United States population. After performing research for these values β, $\frac{1}{\mu}$, $\frac{1}{\gamma}$, $\frac{1}{\gamma_H}$, f_H, and N were able to be found. Meanwhile, the parameters for short and long-term awareness would be experimentally determined via simulation to find the values that allowed the model to fit the data as accurately as possible. The parameter k was chosen to have a value of 2 for each simulation, which is based upon Weitz et al.'s final model and finding that the resulting model is about the same with ranging values 1, 2, and 4 for k.

Since the H1N1 and 2013-2014 flu outbreaks were caused by different strains of the same virus, we felt it appropriate to use the same epidemiological parameters for both diseases. In actuality, the 2013-2014 flu outbreak was less infectious than H1N1 [18], and likely had slightly lower parameters than H1N1. However, we decided that they were not different enough to significantly affect the final model and conclusions. We conducted research to determine the epidemiological parameters for H1N1, and then transferred said parameters to the flu outbreak. This methodology was used because there was a lot more data gathering and research surrounding the H1N1 outbreak than the 2013-2014 flu outbreak, so information about H1N1 was easier to come by. After conducting thorough research [11] [12] [13] [14] [15] [16][17], the specific parameter values for the 2013-2014 flu came out to be β = 0.43 days^{-1} , $\frac{1}{\mu}$ = 2 days , $\frac{1}{\gamma}$ = 6 days, $\frac{1}{\gamma_H}$ = 6 days, f_H = 0.004, N = 30e7 , and k = 2 . Again, k was valued at 2 because of the previous work of Weitz.

After these parameters were determined, two separate models of the number of estimated hospitalizations were generated and plotted. This was overlaid with weekly flu hospitalizations data from H1N1and the 2013-2014 influenza season [18]. With the models and data plotted, the awareness parameters, δ_c and D_c, were altered so the models best matched hospitalization data for H1N1 and the seasonal flu.

Table 2: Parameter values for standard seasonal influenza and H1N1 models

Description	Parameter	Standard Flu Value	H1N1 Value
Transmission rate	β	0.43 days^{-1}	0.43 days^{-1}
Latent period	$\frac{1}{\mu}$	2 days	2 days
Infectious period	$\frac{1}{\gamma}$	6 days	6 days
Hospitalization period	$\frac{1}{\gamma_H}$	11 days	11 days
General hospitalization probability	f_H	0.004	0.004
Total population	N	30*10^7 people	30*10^7 people

Half saturation constant for short-term awareness	δ_c	108e-7 deaths/day per N	90e-7 deaths/day per N
Half saturation constant for long-term awareness	D_c	16500e-7 deaths per N	8000e-7 deaths per N
Sharpness of change in force of infection	k	2	2

Results

Once the model, which integrated awareness, was generated for the COVID-19 parameters to estimate the deaths per day, it was fitted to the daily deaths data for COVID-19 from January 2020 to March 2021 in the United States. The parameters for short-term and long-term awareness were experimentally determined to be 25e-7 and 4000e-7, respectively. As seen in the plot below, the model is accurate for the first outbreak of deaths and the second smaller outbreak as well, but the model doesn't account for the larger outbreak that spikes at the end of the data, though this spike is attributed to extraneous factors, as will be discussed later.

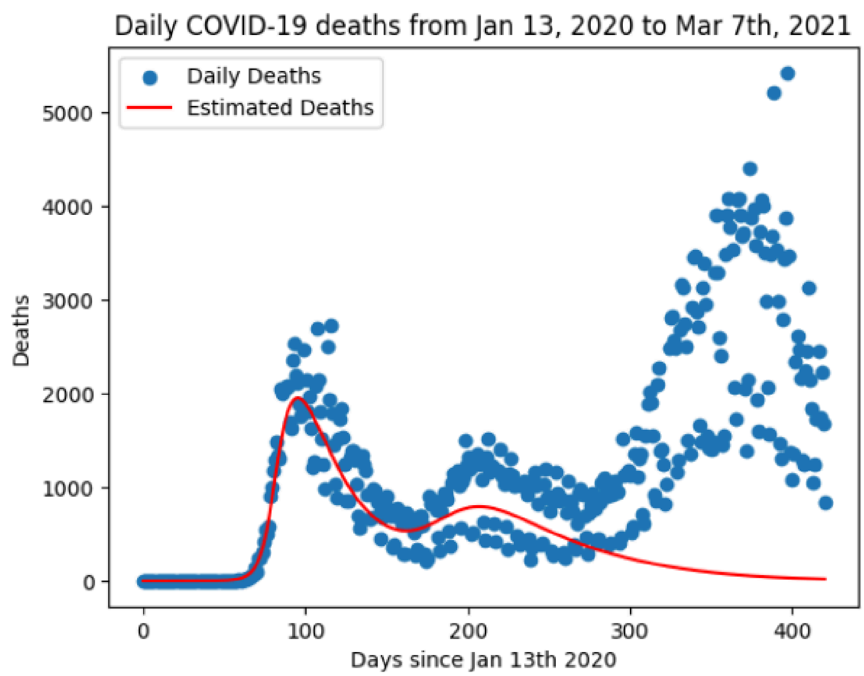

Figure 1: Graph of COVID-19 model related to daily deaths (January 13, 2020 - March 7, 2021)

After the model's viability was confirmed using Weitz et al's COVID-19 parameters, we applied it to H1N1 data. Given the H1N1 parameters, the model was compared to the weekly hospitalizations data of H1N1 from October 2008 to October 2010, around the time of the 2009 H1N1 initial outbreak. The parameters for short-term and long-term awareness were experimentally determined to be 90e-7 and 8000e-7, respectively. As seen in the figure below, the model is able to predict the first outbreak in hospitalizations, as well as the decline, but is unable to predict the larger secondary outbreak. However, as with COVID-19, this secondary spike is also attributed to extraneous factors that will be explored in the discussion.

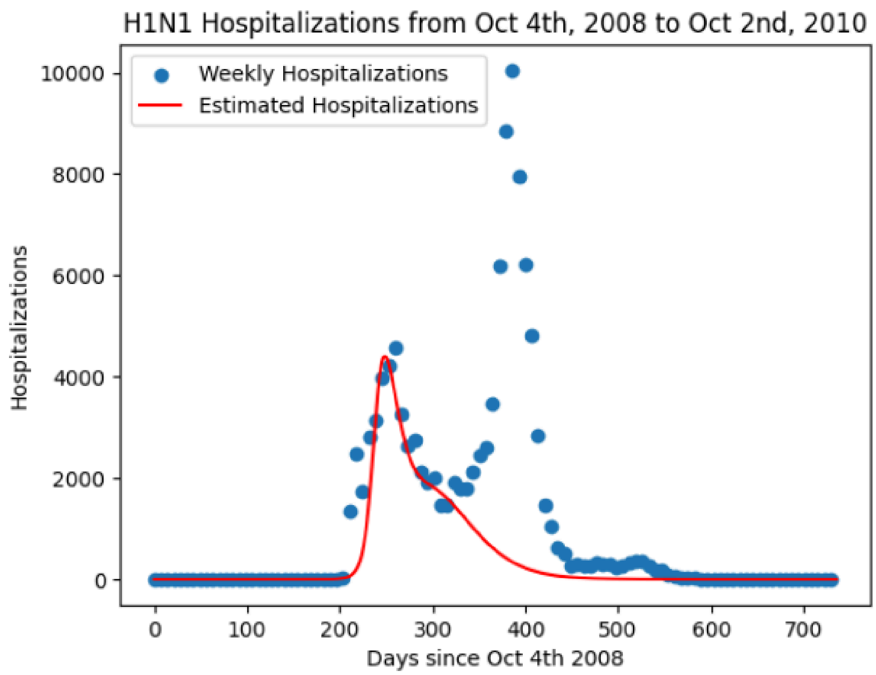

Figure 2: Graph of H1N1 model related to weekly hospitalizations (October 4, 2008 - October 2, 2010)

Finally, the model was used to predict the hospitalizations due to the standard flu season. The model was plotted alongside the weekly flu hospitalization data from October 2013 to September 2014, and the awareness parameters were changed to fit the model to the data. The parameters for short-term and long-term awareness were experimentally determined to be 108e-7 and 16500e-7, respectively. As seen in the figure below, the model is accurately able to predict the first outbreak. The secondary increase in cases is also predicted by the model, but at the wrong time. The model predicts a jump in hospitalizations approximately 25 days earlier than the actual jump in hospitalizations seen in the data. While the timing of the model is inaccurate, we deemed it a success as it accurately represents the overall shape of the graph, just with the incorrect timing (the reasons for which will be provided in the discussion).

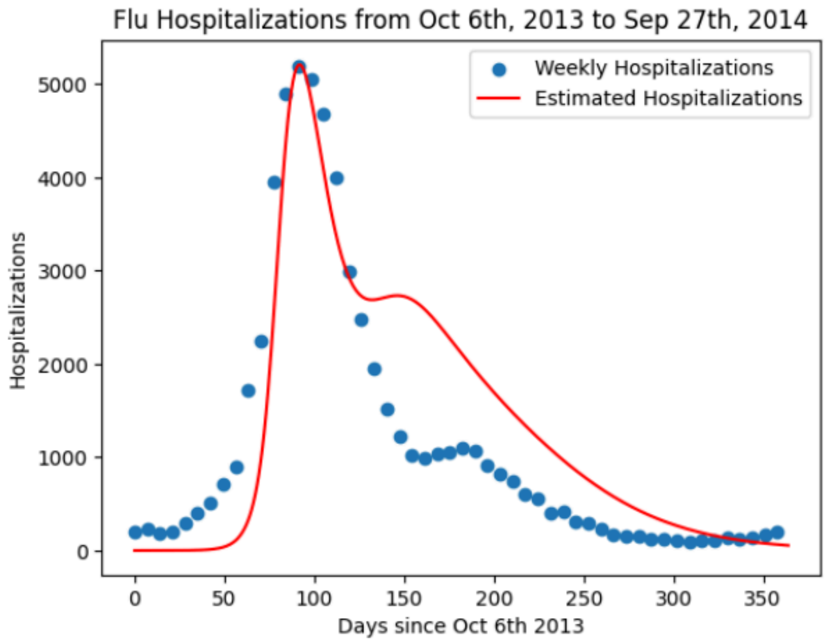

Figure 3: Graph of standard flu season model related to weekly hospitalizations (October 6, 2013 - September 27, 2014)

Discussion and Conclusions

Given that Weitz et al.'s model was originally developed in the context of an ongoing COVID-19 epidemic, it's no surprise that the model fits the existing COVID-19 data very well. With the half-saturation constants for short-term and long-term awareness of 25e-7 and 4000e-7, respectively (750 deaths per day and 120,000 total deaths, respectively), the awareness parameters were much lower than the equivalent parameters for both H1N1 and the 2013-2014 flu outbreak. Intuitively, this makes sense as COVID-19 was a novel, deadly virus that had, at that point, become a worldwide pandemic, and so the public was especially weary of it. The model curve fit the COVID-19 data exceptionally well for the first 250 days, but failed to account for the large spike in deaths that occurred in early November. The spike in COVID-19 cases in early November of 2020 is often attributed to the large number of social gatherings that take place during late October for Halloween [20]. Weitz's et al.'s model was never intended to accurately model the impact of social dynamics, such as increased socialization rate, and thus it is natural that the model fails to account for the large spike in deaths. However, this does not mean that the model is inaccurate. In fact, as can be gleaned from the plot, the model's estimated deaths follow the actual deaths very closely for the first 250 days of the outbreak, thus showing that a population's awareness and the corresponding parameters play an important role in modeling the spread of disease.

After adapting the model to the flu version, we plotted the data of weekly hospitalizations from H1N1 against the model's predicted hospitalizations. The best-fitting model that we generated had half-saturation constants for short-term and long-term awareness of 90e-7 and 8000e-7, respectively (2700 hospitalizations per day and 240,000 total hospitalizations, respectively). These were higher than the parameters for COVID-19, but lower than the ones for the 2013-2014 flu. The model was able to accurately predict the first spike in hospitalizations, however, as with COVID-19, the model was inadequate in predicting the secondary spike of cases. Again, as with COVID-19, the secondary spike in infections can be attributed to extraneous factors. The secondary spike begins in early October, which corresponds to the start of school across America. Given that H1N1 was especially prevalent in children [22], the spike in early fall is sometimes attributed to the start of the back-to-school season [21]. Weitz et al's model doesn't consider the impact of social dynamics, so it is natural that this is unrepresented by our model. Ultimately, however, this model still accurately estimates at least part of the outbreak, which suggests that a population's awareness does have some impact on the spread of disease.

Fitting the model to the 2013-2014 flu outbreak proved to be less straightforward than fitting it to the COVID-19 and H1N1 outbreaks. The best-fitting model that we generated had half-saturation constants for short-term and long-term awareness of 108e-7 and 16500e-7, respectively (3240 hospitalizations per day and 495,000 total hospitalizations, respectively). The model followed the general shape of the hospitalization data, however the model predicted the secondary spike in hospitalizations about 25 days too soon than in actuality. The model predicted a secondary spike based on the fact that the number of daily hospitalizations was going down in the days prior, so the population's short-term awareness decreased, and thus the number of cases increased. Mathematically, this error could be corrected for by increasing the hospitalization period ($\frac{1}{\gamma_H}$), as the hospitalization period is the parameter that controls the 'lag' of the model (as explained in Weitz et al.'s paper [8]). With higher 'lag', the population would take longer to react to the previous decrease in daily hospitalizations, and thus the secondary spike would happen later and in line with the real world data. However, this altered hospitalization period has no basis in reality and we felt that it would be inaccurate to portray it as such. After careful consideration of the context, we hypothesize that the error in the model is due to the fact that hospitalization rate may not be as strong of an awareness indicator as death is. In changing Weitz et al.'s model to estimate hospitalization rate instead of death rate, we altered it in such a way that maintained the awareness impact of death, but replaced death with hospitalization. This means that as far as the model is concerned, a hospitalization has the same impact on awareness as death. Obviously, death is a much more serious consequence than hospitalization, and so the population is likely to care more about it. By having our model portray hospitalization with the same gravitas as death, we likely over attribute the impact that hospitalization has on awareness, which is why the model predicts that the secondary spike occurs earlier than shown in the data. One way to fix this would be to incorporate a constant into the model that represents the ratio of the awareness effect of hospitalization to the awareness effect of death, however, this is beyond the scope of this paper. Ultimately, despite the model's shortcomings in predicting the 2013-2014 outbreak, we still believe that it is useful in demonstrating the impact of the awareness of a population, as the data still follows the general shape of the model as predicted by the awareness parameters.

Ultimately, the awareness parameters for H1N1 and 2013-2014 flu outbreaks followed the predicted trends. They were lower for H1N1 than for the 2013-2014 flu (which means the population had a higher awareness of H1N1), which implies that the population cared a lot more about the H1N1 pandemic than the 2013-2014 flu outbreak, which is consistent with contemporary experience. We found that the model that Weitz et al. proposed for modeling a population's awareness of a disease was at least partially transferable to influenza and H1N1. Though not entirely accurate, the incorporation of awareness parameters into a modified SEIR model was able to predict the amount of hospitalizations due to H1N1 and the 2013-2014 flu outbreak, with some caveats. The lack of accuracy in some sections of the model emphasizes the complexity of real world diseases, and shows that a model based purely on awareness doesn't accurately represent the real world. However, the awareness models were able to account for a significant portion of all three graphs, which confirms the impact that awareness has on disease spread. Our paper concludes that the awareness that a population has towards a disease does affect how diseases spread, and thus should be considered in future modeling of said diseases.

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