

The Impact of Media Coverage on the Transmission Dynamics of Human Influenza

Written by: Jean M Tchuenche, Nothabo Dube,
Claver P Bhunu, Robert J Smith?, Chris T Bauch
Analyzed and Extended by: Jonathan Rub and Tyler King

December 13 2017

1 Abstract

Understanding the spread of disease is an important part of stopping an outbreak. With the rise of information and media there are new ways for people to learn about current events, including disease symptoms and how widespread it is. The original paper tries to model the affect of media with a carrying capacity function which is then edited through optimal control to make a better model. However, when taking real data and trying to data fit the model, the results were not very close. In this paper we used a Poisson distribution to model the interaction between people. We then got a model that resembled the shape that is seen in the real world from data fitting our model to data provided by the CDC.

2 Introduction

Influenza is a highly contagious respiratory illness that is responsible for the deaths of nearly 36,000 people each year. It is a constantly evolving disease that has mutated many times throughout the years, and because of it's many variations it is also one of the hardest illnesses to vaccinate against. The CDC reports that the flu vaccination reduces the risk of contracting the flu by 40 to 60 percent. While this is better than no protection going into the flu season, when comparing the flu vaccine to the effectiveness of other vaccines it ranks amongst the lowest in effectiveness and it is a vaccination that many decide not to get. The CDC reports that in the 2015-2016 flu season, 41.7 percent of adults in the US got their flu vaccination, which means that over half of the adult population of the US foregoes being vaccinated for a seasonal illness that is not only highly contagious but potentially life-threatening.

Being that we now live in the age of information, every flu season more information is readily available to the masses about the severity of the flu each year. Media coverage of the flu can help increase the amount of people that get vaccinated, thus further quelling the influenza outbreak each year and potentially saving thousands of lives. In Jean Tchuenche, Nothabo Dube, Claver Bhunu, Robert Smith?, and Chris Bauch's paper "The Impact of Media Coverage on the Transmission Dynamics of Human Influenza," they explore mathematical models of the transmission of the flu that incorporate the possible influence of mass media outlets. The main logic behind the models is the fact that proliferation of information on emerging diseases can greatly impact individual perception of health risks such as not getting vaccinated for the flu. Their proposed model subdivides the total population into 4 categories, the susceptible, the infected, the vaccinated, and the recovered and incorporates a population density function that continuously decreases the contact rates between the susceptible and infected populations. While their deterministic model is comprehensive and logically sound, it is noted in the paper that further improvements can be made to the model to provide a more accurate model that can successfully emulate real-world transmission dynamics of the flu.

In this paper we discuss the model presented in the aforementioned publication and expand upon the original model to produce a model that more accurately matches real-world data acquired from the CDC. More specifically, we critique the implementation of the media's influence on the model and replace it which

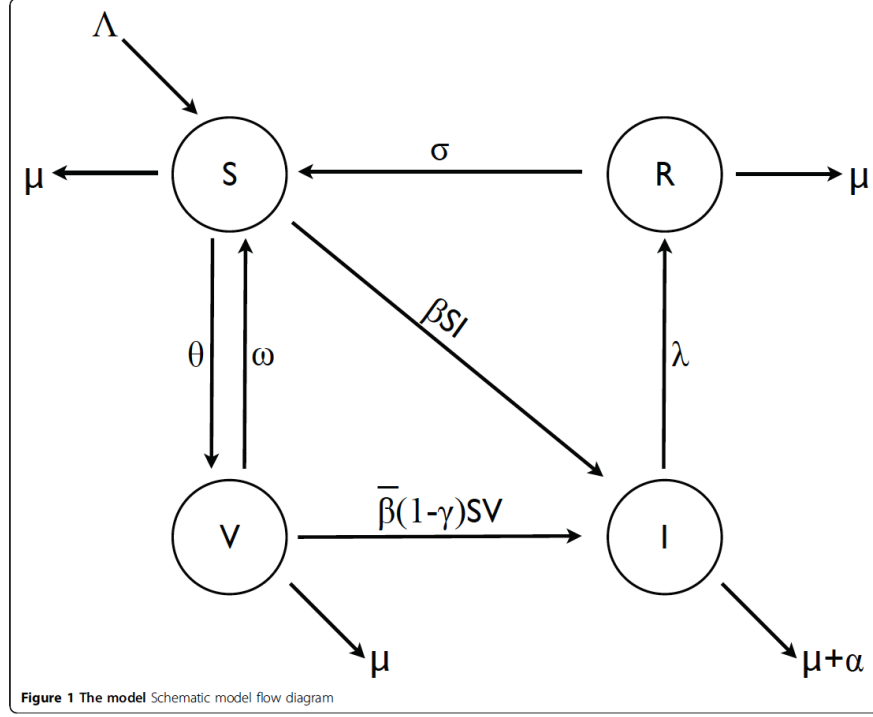


Figure 1: A pictorial representation of the original model

a more statistically driven expression that describes the interactions between the susceptible and infected populations. From there we perform sensitivity analysis on the parameters that can most easily be altered to discuss ways in which our proposed model can better fit the data provided by the CDC. We also employ the optimal control theory techniques presented in the publication to describe an idealistic response of the public to an influenza outbreak that is driven solely by media influence.

3 Discussion of The Original Model

3.1 The Original Model

$$\frac{dS}{dt} = \Lambda + \omega V - (\theta + \mu)S - (\beta_1 - \beta_2 \frac{I}{m_I + I})SI + \sigma R. \quad (1)$$

$$\frac{dI}{dt} = (\beta_1 - \beta_2 \frac{I}{m_I + I})SI + (\beta_1 - \beta_3 \frac{I}{m_I + I})(1 - \gamma)VI - (\alpha + \mu + \lambda)I. \quad (2)$$

$$\frac{dV}{dt} = \theta S - (\mu + \omega)V - (\beta_1 - \beta_3 \frac{I}{m_I + I})(1 - \gamma)VI. \quad (3)$$

$$\frac{dR}{dt} = \lambda I - (\mu + \sigma)R. \quad (4)$$

The nonlinear system of differential equations shown above is the model proposed by researchers that published "The Impact of Media Coverage on the Transmission Dynamics of Human Influenza." Equation 1 represents the rate of change of the susceptible population, equation 2 represents the rate of change of the infected population, equation 3 represents the rate of change of the vaccinated population and equation 4 represents the rate of change of the recovered population. The parameters used in the model are listed in Table 1.

Table 1: A list of the parameters of the original model

Parameters	Designation
Λ	The net influx of people into the overall population via Birth and immigration
ω	The rate at which the flu vaccine's immunity wanes as the flu mutates during the flu season
θ	The rate at which people get vaccinated for the flu
μ	Mortality rate due to natural causes other than the flu
$\beta_{1,2,3}$	The contact rate between different sub-populations (a mass action parameter)
σ	The rate at which the natural immunity acquired by recovering from a strain of the flu wanes as the flu mutates during a flu season
γ	The immunity granted by the flu vaccine represented by a decimal between 0 and 1.00
α	The mortality rate associated with succumbing to the flu
λ	The recovery rate of the flu
m_I	the half saturation constant that reflects the impact of media coverage on the social interactions between different sub-populations

3.2 The Logic Behind the Original Model

This model is an open model that allows for different initial and final total population numbers, in which the difference between the two is caused by deaths during the flu season due to the flu and/or natural causes. Any members that enter the total population are assumed to not be vaccinated nor recovered from a previous flu illness. Due to the fact that the flu vaccine can't protect against new strains of the flu that emerge during the flu season that the vaccine is administered, members of the vaccinated population become susceptible again at a rate ω . Also, due to the many possible mutations of the flu during a flu season, those that have recovered from the initial flu strain become susceptible to the flu again to the different strains of the flu at rate σ . Members of the susceptible population leave when they get vaccinated at rate θ , die of natural causes at the universal mortality rate μ , or become infected through contact with the infected population. The interaction between the infected and susceptible populations is the first place where the impact of the media is implemented in the model. The β_1 parameter describes the rate of contact between the infected and susceptible populations in the absence of media coverage. β_2 is a contact rate equal to or slightly less than the original contact rate and it is multiplied by the population density function:

$$g(I) = \frac{I}{m_I + I}. \quad (5)$$

The function $g(I)$ has an upper bound of 1 and approaches 1 as the infected population increases. When the infected population increases the β_2 contact rate slowly approaches the original contact rate and since it is subtracted from the original contact rate, the overall mass action contact rate diminishes to zero. In the real world this can be manifested through public health initiatives akin to that of Chicago 1918 during the height of the Spanish flu pandemic. People were advised to avoid public outings and were even arrested for risking the production of fomites (objects contaminated with infectious agents), most notably by spitting in public.

People enter the infected population from the susceptible population through the mass action rate previously described and from the vaccinated population by a similar expression except at a considerably lesser rate due to the $(1 - \gamma)$ term that introduces the immunity granted by the flu vaccine. People leave the infected population through death from natural causes μ , death due to disease α , and recovery from the disease λ .

The vaccinated population increases due to people from the susceptible population getting vaccinated and decreases from people getting infected despite being vaccinated.

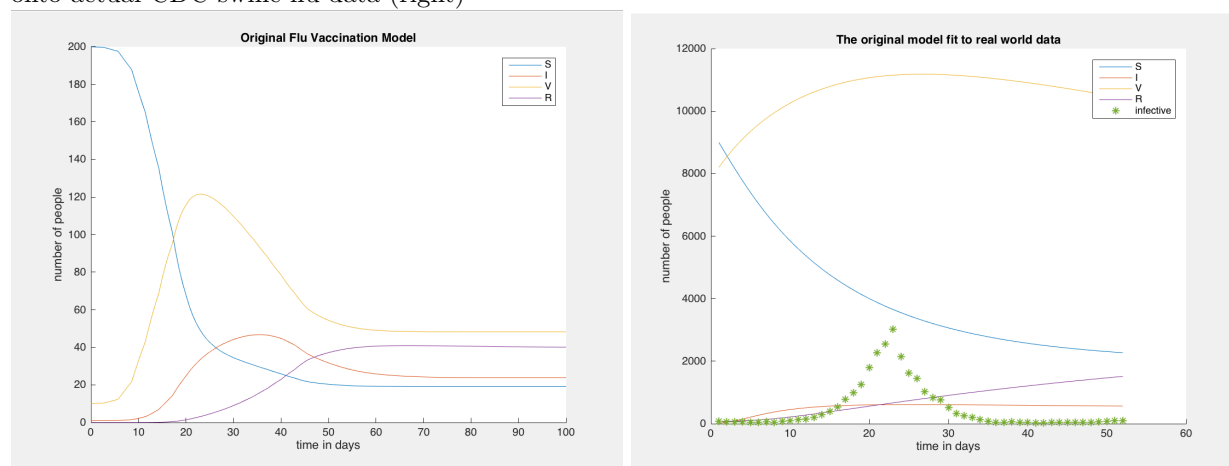
The recovered population increases from people recovering and decreases from death due to natural causes and the re-susceptibility rate σ .

3.3 Critiques of the Original Model

The two main issues with this model are the way the media's impact is represented in the model and upon the numerical calculations of the model, the final states of the sub-populations.

Regarding the implementation of the media model, specifically $g(I)$, while the population density function produces results similar to what is seen in real life, there wasn't any explanation of why the method used was mathematically correct. In fact when this model is run on a simulation population of 211 people some peculiar results arise.

Figure 2: Simulation population of 211 people (left) and the simulation population of 20,000 superimposed onto actual CDC swine flu data (right)



As you can see from Figure 3.3, the model implies that around 20 people remain infected with the flu for a period of about 40 days, which is impossible because if the flu doesn't kill you it goes away in about a week. This model, while comprehensive, is inaccurate. When superimposed onto actual CDC data pertaining to the amount of people that were infected with the H1N1 strain, the results from the model don't come anywhere near the actual data.

From the CDC data we see that the infected population dynamics during the flu season resembles that of a Gaussian curve, which implies the use of an exponential term within the description of the infected population. This is where we make our improvement on the model. The way in which we incorporate the media's impact is similar in the fact that it acts by diminishing the contact rate between the infected and susceptible populations. In terms of how it is implemented, we choose to incorporate a diminishing exponential into the infected differential equation in place of the $g(I)$ population density function. When the system is solved it yields a solution for the infected population curve that resembles the curve that produces the Gaussian integral, thus more closely resembling the data.

4 Discussion of Our Proposed Model

4.1 The Model

$$\frac{dS}{dt} = \Lambda + \omega V - (\theta + \mu)S - \beta_1 e^{-a_r I} SI + \sigma R. \quad (6)$$

$$\frac{dI}{dt} = \beta_1 e^{-a_r I} SI + \beta_1 (1 - \gamma) VI - (\alpha + \mu + \lambda)I. \quad (7)$$

$$\frac{dV}{dt} = \theta S - (\mu + \omega)V - \beta_1 (1 - \gamma) VI. \quad (8)$$

$$\frac{dR}{dt} = \lambda I - (\mu + \sigma)R. \quad (9)$$

In order to incorporate the exponential required to produce the Gaussian curve, we multiply the initial contact rate by the Poisson distribution expression $e^{-a_r I}$, where a_r is a constant that represents severity of the media's coverage. We also make the assumption that once vaccinated, people interact with the infected at the same rate as they did at the start of the flu season. All other parameters remain the same from the original model with the exclusion of m_I which is omitted from the model since the $g(I)$ function is not used. Qualitatively, the Poisson distribution term describes the probability of not coming into contact with an infected individual, but as the number of infected individuals increases, the likelihood of encountering an infected individual increases, thus making the susceptible population more cautious. Incorporating a Poisson factor also makes sense because we know that the average amount of interactions a person has a Poisson distribution. The severity constant thus acts as a multiplier that can describes the exaggeration or lack of coverage on a particular flu season. During the 2009 outbreak of swine flu, many media outlets exaggerated the extent of the severity of the outbreak saying that a global pandemic was eminent. While this widespread panic did have a negative impact on the economy, as the CDC data shows, the outbreak was quelled within a matter of 2 months. From a purely epidemiological standpoint, the H1N1 awareness campaign was a success mainly due to the mass hysteria caused by mass media outlets.

4.2 Sensitivity Analysis

After the model was created, we performed sensitivity analysis on the three parameters that are most likely to be affected by the media which are the rate of vaccination θ , the initial contact rate β_1 , and the severity of coverage a_r . As can be seen by Figure 4.2, the parameter that has the greatest impact on reducing the infected population is the severity of coverage, thus when fitting the model to the CDC swine flu data, it is possible to calculate an estimate of the severity parameter most associated with the 2009 out break of swine flu due to the fact we can fit the data by relying solely on the severity constant. From this parameter value, which represents the over-exaggerated case, we can compare and contrast different severity constants that provide the greatest amount of impact with the least amount of economic cost. Finding the perfect severity constant value that fits the criteria aforementioned becomes the basis of the possibility of optimal control for our model

4.3 A Brief Discussion of the Optimal Control of our Model and the Ideal Media Response to the Flu

In the publication, the researchers expanded upon their own model by adding controls to their model that represent intervention methods that can be employed to influence the overall performance of the media's campaign. The optimal performance of their model is described by the objective functional J.

$$J = \int_{t_0}^{t_f} [S(t) + V(t) - B_1(I(t)) - B_2(u_v^2(t) - u_m^2(t))]dt \quad (10)$$

The objective functional is to be maximized, which in this case means maximizing the susceptible and vaccinated populations while minimizing the infected populations as well as minimizing the overall cost of intervention. The functions $u_v(t)$ and $u_m(t)$ represent the controls that operate on the vaccination rate and

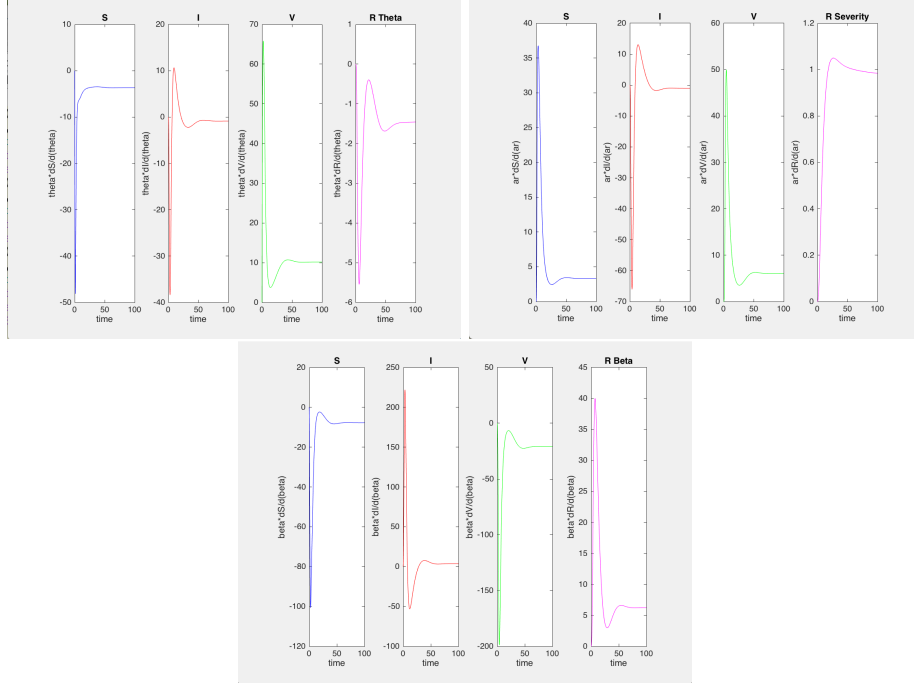


Figure 3: Sensitivity functions of θ , a_r , and β_1 respectively

the media's influence respectively in the original model while the parameters B_1 and B_2 represent weight constraints or coefficients that balance out the units of Equation 10 to yield dollars expended over time.

For our model the objective takes the form:

$$J = \int_{t_0}^{t_f} [S(t) + V(t) + B_1(S(t) + I(t) + V(t) + R(t)) - B_2(I(t)) - B_3(u_m^2(t))]dt \quad (11)$$

in which $u_m(t)$ is the media control variable that is to be multiplied by the severity constant that adjusts the parameter to the appropriate value that provides the greatest impact on the public, whilst providing the least impact on the revenue generated by the interactions between people within the total population represented by $B_1(S(t) + I(t) + V(t) + R(t))$, due to the costs of treatment for the sick, $B_2(I(t))$, and the costs of the media intervention $B_3(u_m^2(t))$. By adding a time variant control on the severity of the media's coverage, a_r increases when the infected population spikes during the peak of flu season and decreases after the moderated media impact manifests itself as a more cautious public thus nullifying the potential for an influenza panic similar to that of the 2009 H1N1 outbreak.

4.4 Further Improvements on Our Model

While our model clearly the CDC swine flu model better than the original model, problems still arise with the numerical calculation of the population dynamics of our model that leave room for improvement.

One flaw can be seen upon examination of Figure 4. The model produces results that indicate that more people recover from the flu, than actually get the flu which is physically impossible. A possible reason for this is a misrepresentation of recovery from the flu in our model. Since the flu only lasts about a week, the proper way to represent recovery from the flu involves using an expression that moves members from the infected population to the recovered population after 7 days.

Another way in which our model can be improved is the acquisition of more data on the amount of people that get vaccinated and recover from the flu. More specifically, data coming from research pertaining to the amount of people that receive flu shots and the amount of people that recover from the flu day by day during the flu season. With that data, we can fit the other sub-populations to real world data, thus providing us with more accurate parameter values for modeling the flu.

5 Data Fitting our Model

Using our model, equations 6 - 9, we took real world data for other parameters and created Matlab code to fit the data to infected data taken from the CDC. In regards to the parameters used, since in 2015-2016 the effectiveness of the flu vaccines was 48%, γ was 0.48. All other parameters were derived through similar means.

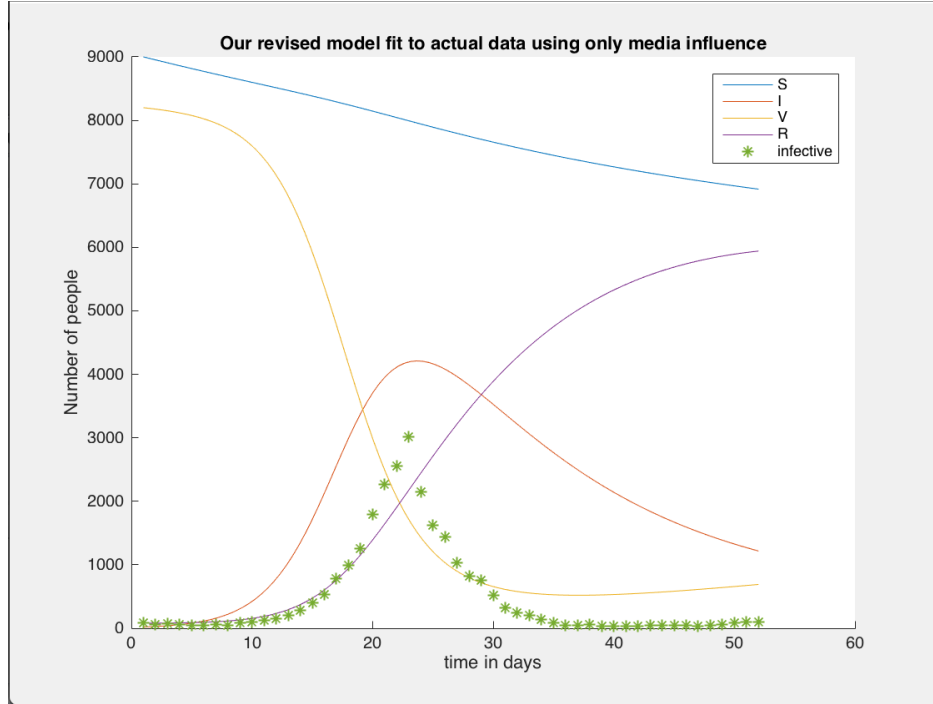


Figure 4: Using the model we are proposing we took data for infected individuals from the CDC and fit the a_r value so that the model could be as close to real life data as possible

Looking at Figure 4 the model fitted to the data we can see the overall shape of the Infected population is similar to the real life data. This is much better than the model the paper proposed where the data is not fit very well at all. In our model there is a drop in vaccinated individuals, which can be attributed to the effectiveness of the disease and the rise of the recovered population.

Initially we attempted to fit all the parameters to the data, but since there are a large number of parameters we did not have the processing power nor the time to let the program run to fit the data. Therefore, we looked up values for the 2015-2016 influenza season to create the most realistic model with the available resources. We ended up only fitting a_r because we wanted to see if the model with real values and our additional term could yield results similar to the expected results.

The a_r value that we found was 0.95. This value represents the tone of the media coverage on the flu. Since the Poisson distribution represents the probability of not running into an infected person and as that probability decreases so does the contact rate, the a_r value describes how the media portrays the risk of infection. In this case it means that the media coverage was very severe.

Looking at the model we made one of the concepts we can look at to improve the data fitting and model in general is having more data on people who are vaccinated and susceptible to be able to fit the model to that data as well. Also looking at the graph it seems counter intuitive that the vaccinated population would decrease as the infected and recovered populations increase. I think this is due to the low effectiveness of the vaccination. Having a better computer to run the data fitting on more parameters could also help create a much better model.

6 Conclusion

Upon analysis of the model presented in the publication, we were able to develop an updated deterministic model describing the media's affect on the transmission dynamics of the flu. This was done by incorporating a statistical expression known as a Poisson distribution to describe the ways in which the media influences the public's perception of the risk of infection, thus altering the public's behavior in such a manner that suppresses an influenza outbreak. The Poisson distribution represents the media's portrayal of the individual risk of infection and because of this edit to the original model, we were able to produce a model that better emulated real world data regarding the population dynamics of those infected with the H1N1 strain of influenza. When fit to the data using the controllable parameters Θ , β_1 , a_r , and m_I , the original model returns a sum of squares value of 5,029.9 while our model returns a sum of squares value of 4,410.0 which implies that our model is 12 percent better at emulating real world data than the original model.

While performing sensitivity analysis on our proposed model we found that the severity constant, a_r , was the parameter that most directly influenced the prevention of infection from the flu even more so than the rate at which people get vaccinated from the flu! Thus implying that national public health initiatives perpetuated by the media are more effective when it comes to the prevention of the spread of the flu than the flu vaccine itself. Using optimal control techniques, further research can be done on our model to provide crucial information on the ways the media should portray the flu during a flu season in order to ensure the maximal well-being of the general public while also limiting the economic impact of the campaign.

References

- [1] Heidi J Larson, David MD Smith, Pauline Paterson, Melissa Cumming, Elisabeth Eckersberger, Clark C Freifeld, Isaac Ghinai, Caitlin Jarrett, Louisa Paushter, John S Brownstein, Lawrence C Madoff. "Measuring vaccine confidence: analysis of data obtained by a media surveillance system used to analyse public concerns about vaccines." *The Lancet Infectious Diseases* (2013). Website.
- [2] Jean M Tchuenche, Nothabo Dube, Claver P Bhunu, Robert J Smith?, Chris T Bauch. "The impact of media coverage on the transmission dynamics of human influenza." *BMC Public Health* (2011). PDF.
- [3] Shannon Collinson, Kamran Khan, Jane M. Heffernan. "The Effects of Media Reports on Disease Spread and Important Public Health Measurements." *PLOS* (2015). Website.
- [4] Smith, Richard D. "Responding to global infectious disease outbreaks: Lessons from SARS on the role of risk perception, communication and management." *Social Science Medicine* (2006): 31133123. Website.
- [5] Walzer Leavitt, Judith. "Public Resistance or Cooperation?" *BIOSECURITY AND BIOTERRORISM: BIODEFENSE STRATEGY, PRACTICE, AND SCIENCE* (2003): 185-192. PDF.
- [6] Center for Disease Control and Prevention. Weekly U.S. Influenza Surveillance Report. 6 Decemeber 2017. WebPage. 6 Decemeber 2017.