# From Cyber Space Opinion Leaders and the Diffusion of Anti-vaccine Extremism to Physical Space Disease Outbreaks

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**Abstract.** Measles is one of the leading causes of death among young children. In many developed countries with high measles, mumps, and rubella (MMR) vaccine coverage, measles outbreaks still happen each year. Previous research has demonstrated that what underlies the paradox of high vaccination coverage and measles outbreaks is the ineffectiveness of "herd immunity", which has the false assumption that people are mixing randomly and there's equal distribution of vaccinated population. In reality, the unvaccinated population is often clustered instead of not equally distributed. Meanwhile, the Internet has been one of the dominant information sources to gain vaccination knowledge and thus has also been the locus of the "anti-vaccine movement". In this paper, we propose an agent-based model that explores sentiment diffusion and how this process creates anti-vaccination opinion clusters that leads to larger scale disease outbreaks. The model separates cyber space (where information diffuses) and physical space (where both information diffuses and diseases transmit). The results show that cyber space anti-vaccine opinion leaders have such an influence on anti-vaccine sentiments diffusion in the information network that even if the model starts with the majority of the population being pro-vaccine, the degree of disease outbreaks increases significantly.

**Keywords:** Agent-based modeling · Information networks · Infectious disease transmission

## 1 Introduction

Measles is a highly contagious disease and poses danger to communities around the world. Even though a safe and cost-effective vaccine has been available, we are still experiencing measles outbreaks every year in developed countries. Researchers and health practitioners have realized the potential danger of smaller clusters with high density of unvaccinated children (Lieu et al. 2015). In the US, the main cause of measles outbreaks is not the availability or affordability of vaccines but belief systems of individuals, which is seen with the advent of vaccine exemptions (May and Silverman 2003). The vaccine refusal rate is becoming higher in the last few years as non-medical exempt policies are being implemented (Wang et al. 2014). The fear with respect to the safety of the measles, mumps, and rubella (MMR) vaccine is the main argument behind


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the “anti-vaccine movement.” How anti-vaccine parents formed their opinions and how to prevent more parents from distrusting vaccination have become questions more important than ever. This paper explores the influence of anti-vaccine opinion leaders in cyber space and the consequences in disease outbreaks if the influence is carried over to physical space communities. An agent-based model (ABM) is developed to unveil mechanisms and causal relationships between opinion leaders, opinion clustering, and the degree of disease outbreaks.

## 2 Background

A large amount of research has been dedicated to exploring the driving force of anti-vaccine sentiment. With the advent of the Internet and social media platforms, parents search for information about MMR vaccine online (e.g. Kata 2012). Even a brief encounter of vaccine-critical websites could increase perceptions of risk of vaccinations and a decrease in the perception of vaccination benefits (e.g. Betsch et al. 2010). To better understand the multi-folded impact of online vaccine information, however, we should understand the “network effects” of vaccine information flow (Witteman and Zikmund-Fisher 2012). For instance, the fact that small groups of vocal “anti-vacciners” leveraged the power of social media to keep the ban on personal belief exempt bill of California from passing (DiResta and Lotan 2015). To date, little research has focused on the influence of online opinion leaders’ gains on vaccination sentiments. Online opinion leaders are those who have disproportionally big advantage on disseminating their own voices and opinions. They are not necessarily celebrities in real life, but structurally, act as “hubs” in scale-free social media networks. It has been shown for example, that the retweet network of Twitter is a scale-free network (Tinati et al. 2012). This allows the influential users to be “opinion leaders” (Van Eck et al. 2011).

As the purpose of this paper is to connect opinion clustering to disease outbreaks, a prototype model must be mentioned, that of Salathé and Bonhoeffer (2008) who explored the effect of opinion clustering on disease outbreaks. The mechanism in their work was simple: 100 agents were created in a lattice network and each one was assigned a vaccination opinion (either support or oppose). After the opinion formation process, anti-vaccine agents were clustered together. Their model well demonstrated that a small clustering effect could increase the probability of a disease outbreak. The opinion formation process was probability-based, whereby an agent’s choice for support/oppose was decided by two factors: the number of neighbors with opposite opinions (i.e. a dissimilarity index) and the parameter named “strength of opinion formation”. Our model substitutes this probability based opinion formation process with one that simulates opinion diffusion in networks triggered by opinion leaders.

## 3 Methodology

The agent-based model was implemented in NetLogo 5.3.1. A brief model description is given below which loosely follows the ‘ODD’ (Overview, Design concepts, and Details) protocol (Grimm et al. 2010). A more comprehensive and in-depth description of the model and source code can be found at https://www.openabm.org/model/5509/. Agent-based modeling allows exploring interactions among heterogeneous agents. By systematically changing initial conditions, the model simulates different scenarios (i.e. the different number of anti-vaccine opinion leaders and different level of anti-vaccine sentiment of the others). The main purpose of our model is to simulate how anti-vaccine extremism sentiment diffuse from anti-vaccine opinion leaders in a scale-free network and how this diffusion process creates anti-vaccine opinion clusters that gives rise to disease outbreaks.

### 3.1 Agents and Environment

The agents are heterogeneous individuals with different levels of anti-vaccine sentiment level, physical locations, connection status in the cyber network and other attributes in Boolean logic format – extremist or non-extremist, vaccinated or not vaccinated, susceptible or not susceptible, infected or not infected, recovered or not recovered. The environment of the model is two folded: physical space and cyber space. Agents are connected differently in either space. The physical space is represented by lattice. Each grid cell on the lattice is one physical location, which does not represent any real world geographical area but only an abstraction. This model does not consider different population densities and all the grids are occupied. The world is wrapped both horizontally and vertically. The neighborhood is a Moore neighborhood in that each individual has eight neighbors who are located in the most adjacent eight grids.

### 3.2 Process Overview and Model Scheduling

There are five steps processed one by one for each run (see the details in Sect. 3.1 in the ODD): Step (1) creates the scale-free cyber network, assign each one an anti-vaccine sentiment value (the distribution is a parameter), and identify a certain number (parameter) of the most connected individuals to be anti-vaccine opinion leaders. In step (2), those who are directly connected with opinion leaders in the cyber network and have an anti-vaccine sentiment value higher than a threshold (parameter) become extremists which allows extremism to spread. In our model, "Directly connected" means one-degree connection in the network. Followers of followers, for instance, do not get influenced by opinion leaders in the cyber network. This process is only executed once in the model for each run. In step (3), we spread extremism in physical space after the spread on cyber space is established, those who are extremists influence their local neighbors with the same diffusion mechanism as in step 2. Following this in step (4) we capture vaccination rates in the sense that extremists are those who are not willing to get vaccinated while the rest of the population gets vaccinated and is immune from the disease. Those who are not vaccinated are "susceptibles". Finally, in step (5) we model disease transmission for which we use a SIR (Susceptible-Infectious-Recovered) disease transmission model. Vaccinated individuals and those who are recovered are all treated as being immune from the disease. For each time step, not everyone who are susceptible and have infected neighbors will be infected as infection only happens under certain probability/rates. There is also a recovery rate for infected agents (this is discussed further in Sect. 3.1 of the ODD). The model does not consider death and every infected person recovers. The model stops when nobody can be infected any more. “Time” is not counted until the model enters disease transmission part. Each time step, the model records of the number of infected agents, susceptible agents, and recovered agents to allow for further analysis.

### 3.3 Initialization

In the initial state of the model, contains 2601 (51 * 51) grid cells and individuals (i.e. agent) are created on each grid cell. Default values of the individuals include: the attribute “anti-vaccine-sentiment”, which follows a normal distribution with a mean of 0 (overall the sentiment is neutral) and a standard deviation of 1 with an upper bound 1 and a lower bound –1. If it’s positive, it means that this agent is opposed to vaccination and negative means supportive. All the agents are initialized as non-extremists and all their attributes related to disease transmission, “vaccinated?”, “susceptible?”, “infected?”, “recovered?” are set as false.

In addition, the infection rates and recovery rates functions are also set up as the model initiated. For each agent, the infection rates are calculated based on the exponential function: $f(i) = 1 - \exp(-ßi)$. The function is from the above-mentioned prototype model by Salathé and Bonheoffer (2008). In all the simulations, $ß = 0.05$ and i represents the number of neighbors that are infected. Because the exponential distribution is fat-tailed, the infected probability will increase faster as the number of infected neighbors increases. The recovery rate is 0.1% for all agents. The start of the disease transmission is always from 2 randomly picked agents. Three parameters need to be specified to initialize the model: number of individuals connected in the network, number of opinion leaders, and the sentiment threshold.

## 4 Results

Before presenting the results, it needs to be noted that sensitivity testing of the model parameters and verification was performed to ensure the model was functioning as expected. To control the impact of other factors, in each experiment, the cyber network remains the same. Simulation experiments were carried out to compare the result of “experimental group” – experiments with the process of sentiment diffusion; and the “control group” – experiments without the diffusion process. To make it comparable, after the spread of sentiment in cyber network, there’s a number of anti-vaccine extremists and the control group is constructed that use the number of anti-vaccine extremists from experimental group but picked randomly. For both experimental and control group, we randomly pick 2 agents as infected and spread the disease in the physical space. For each run, output the maximum number of people who are infected for each group. We experiment with two parameters: number of opinion leaders = [1, 2, 3, 4, 5, 10, 15, 20, 30] and sentiment threshold = [0.95, 0.9, 0.85, 0.8, 0.75, 0.7, 0.65, 0.6, 0.55, 0.5]. For each combination, 100 simulations were carried out for experimental and control group.

Our main finding, as shown in Fig. 1, is that even when the sentiment threshold is high, the clustering effect of disease transmission is still strong. Having a high sentiment threshold means that only a small proportion of the population is potentially extremists. For instance, when the parameter is 0.95, it indicates that only 5% of the model population has the possibly to be turned into anti-vaccine extremists. Even in this strict condition, the increase of the maximum number of infected is higher than 33%. This shows that when the majority population is pro-vaccine, there's still serious potential danger from small unvaccinated clusters. Additionally, what's surprising is that the increase in the maximum number of infected people is the largest when the number of anti-vaccine opinion leader is equal to one. When there's only one opinion leader in the network, the unvaccinated clusters are denser than those created under the influence of more than one opinion leaders. As the number of opinion leader increases, the model ends up having unvaccinated clusters that are more dispersed, which is structurally more like the randomly picked unvaccinated population (the correspond control group) and therefore, there's lower increase of maximum infected population.

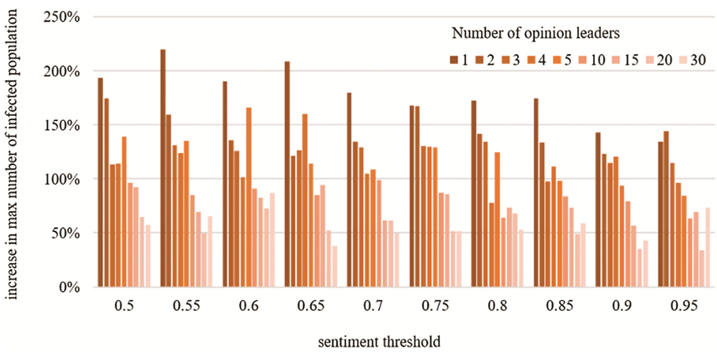


**Fig. 1.** Results of simulation experiments

## 5 Discussion

The model explores the two-folded influence of online anti-vaccine opinion leaders, i.e. the potential influence on cyber level opinion change and those being influenced by opinion leaders could become influencers themselves in their own physical community. Our major finding is that while the majority of the population is pro-vaccine, with very few online opinion leaders triggering the spread of sentiment of anti-vaccination, unvaccinated clusters in physical space can lead to a drastic increase in infection comparing to the scenario that unvaccinated population is not clustered. This model, however, is a simple model with assumptions that simplify real world scenarios but it is a foundation for our ongoing work that analyzes Twitter anti-vaccine textual data and the user retweet network. As for the model itself, one of the limits is that it only considers social influence. The phenomenon of opinion clustering can be both the result of social influence and homophily, which is often treated as being coupled together to create clusters in network theory (Shalizi and Thomas 2011). With this being said, this paper explores the possibility of analyzing anti-vaccination opinion formation by taking social network attributes and social influence into consideration. Considering the growing trend in online health knowledge seeking and the increasing influence of anti-vaccine movement on various social network websites (e.g. Kata 2012), our model lays the foundation study the nexus of cyber and physical relationships and provides a heuristic tool to study how anti-vaccine opinion leaders potentially increase the severity of measles or other preventative disease outbreaks.

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