Overcoming Vaccine Hesitancy by Multiplex Social Network Targeting

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Abstract. Understanding the impact of social factors on disease prevention and control is one of the key questions in behavioral epidemiology. The interactions of disease spreading and human health behavior such as vaccine uptake give rise to rich dueling dynamics of biological and social contagions. In light of this, it remains largely an open problem for optimal network targeting in order to harness the power of social contagion for behavior and attitude changes. Here we address this question explicitly in a multiplex network setting. Individuals are situated on two layers of networks. On the disease transmission network layer, they are exposed to infection risks. In the meantime, their opinions and vaccine uptake behavior are driven by the social discourse of their peer influence network layer. While the disease transmits through direct close contacts, vaccine views and uptake behaviors spread interpersonally within a long-range potentially virtual network. Our comprehensive simulation results demonstrate that network-based targeting with initial seeds of pro-vaccine supporters significantly influences the ultimate adoption rates of vaccination and thus the extent of the epidemic outbreak.

Keywords: Multilayer networks · Network-based interventions · Influence maximization · Opinion formation · Epidemic models

1 Introduction

According to WHO, vaccine hesitancy—the reluctance or refusal to vaccinate despite the availability of vaccines—jeopardizes the progress made in combating vaccine-preventable diseases and was listed among the ten threats to global health in 2019 along with air pollution, climate change and global influenza pandemic [35]. Paradoxically, vaccine hesitancy has became a particularly big problem in high-income countries that manifests itself in the growing decline of trust in experts, the state, corporations, and media [21]. Unsurprisingly, vaccine hesitancy should not be underestimated in the current COVID-19 pandemic as

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well [6,11,18]. Overcoming vaccine hesitancy has became a serious issue in the era of worldwide use of social media [23,27]. In particular, negative experiences like side-effects of vaccination spread quickly and undermine trust in medical care. As observed in [33], individual's vaccination decision depends in part on that of those surrounding the social network. Modeling and studying the interaction between the social environment and vaccination behavior, and thus the dynamics of a disease spread remains therefore an active research topic. Approaches from evolutionary dynamics [5,8], game theory [36], decision-making [3] come into use; we refer to [1,2] for an overview. Regardless of the methods, there are two further distinctions that can be made. On the one hand, the surrounding infrastructure—either both social and epidemic aspects are considered within one network or each one has its own environment. On the other hand, the vaccination strategy—the individuals are motivated to vaccine either by information campaign or by the apprehension of getting infected. The separation between the social and epidemic environment allows capturing the different dynamics of the processes driven thereon as well as the interaction between them. Prior work has made a number of advances on studying such disease-behavior interactions, including: a two-stage game with vaccination decision followed by the health outcome on an epidemiological process [8,13], an immunization strategy based on vaccination sentiments shared on Twitter and applied to a network with a spreading infection [32], a 2-layer network where diffusion of an infectious disease on one layer interacts with diffusion of preventive behavior on the other [25], or—supplemented by an information diffusion layer—a 3-layer network [24], and a stochastic agent-based model for influenza transmission associated with vaccination uptake considered as a socially contagious process [20]. Here, we consider a two-layer multiplex, one with a social communication network and one with a disease transmission network. The novelty of our approach is twofold. Unlike [4], which modeled public opinion formation and the spread of infectious disease as two serial processes that occur on the same contact network, we assign a separate layer of contacts to each of the processes and thus consider a multiplex. Additionally, in some previous multiplex approaches, the spreading processes taking place on the layers are of the same kind, e.g. opinion formation on different social networks [29] or diffusion or epidemic spread in complex networks [7,10,14,25,30,37]. In contrast, we consider transmission dynamics of different sorts. There is active ongoing research on how to use social media influencers for advertisement or health campaigns [17,22]. Over the years, various strategies have been developed to identify those individuals in a network who contribute to a maximal spread of information. This includes tracking the values of network centralities like degree and betweenness centrality [31], eigenvalue centrality for community structured networks [26], other community-based strategies [15] or following random acquaintances [9,32]. Generally, intrinsic motivation is more fruitful than that caused by fear. The same applies for vaccination. In addition, prophylactic vaccinations can prevent the outbreak of an epidemic if the pro-vaccine campaign has started sufficiently in advance [12]. Therefore we opt for a word-of-mouth vaccination campaign and trigger on the layer of social communication network with an opinion formation process. We propose a multiplex network framework to investigate the impact of an ongoing vaccine sentiments on epidemic spreading. Our contribution is structured as follows. First, we specify the structure of the layers of the multiplex as well as parameterize the dueling contagion processes on them. Next, we set up modeling scenarios and discuss their implications, followed by conclusions with an outlook.

2 Model

The multiplex we consider consists of two layers having equal sets of individuals but differing in the connections between the individuals. One layer represents the local community environment of an individual, where the person physically encounters family members, coworkers, friends and other people at leisure times or hobbies. We assume a uniform distribution of the number of these contacts for all individuals and thus represent these relationships with a two-dimensional lattice graph. In this environment, a disease dissemination process is emulated. On the other layer, we use a social network with non-local links, which provides a platform for opinions exchange. On this opinion network layer, the connections between the individuals are built on the basis of the Barabási-Albert graph. Its structure provides an environment in which an agent's network position affects the dynamics of the dissemination of opinions. It is known that scale-free networks enhance both the vaccination behavior and thus the effective immunization [5].

Algorithm 1: The simulation

Input: All parameters listed in Table 1.

Initialize the multiplex with a grid graph and the Barabási-Albert graph.
Set up the opinion layer on the Barabási-Albert graph and the disease layer on the grid graph.
while *more infected individuals than at start* **do**
  Select randomly an individual.
  if $rand() < \omega$ **then**
    Update the state of the individual on the disease layer.
  else
    Update the state of the individual on the opinion layer.
  end if
end while

Output: The state of each individual per iteration and layer.

The spread of the disease on the one layer and the opinion formation on the other take place alternately during a simulation run. With every iteration, one individual is chosen uniformly at random. The next step is to select the layer on which the respective process is to be continued. Since the processes that run separately on the two layers have different dynamics, the probability of choosing a layer does not need to be the same. For that we introduce the first parameter ω and refer to Table 1 for the overview of all model parameters for the agent-based simulation. Once the layer is chosen, the corresponding process is continued according to the state of the individual in this layer as is explained below in detail.

2.1 The Opinion Layer

Our interest is to qualify the effects of the willingness of the population to prevent an epidemic through vaccinations. Therefore, we simulate an exchange of views on the subject of vaccines. Based on the way the agents represent their opinions, we consider a voter model with single discrete variable with more—in our case three—states, according to the classification given in [19,34]. In our setting, an individual can have one of the three discrete opinions: counter, neutral or pro, indicated by the values $-1, 0$ and 1 respectively. The number of supporters and opponents at start is given by the parameters υ^+ and υ^- respectively. To compare the impact of the supporters' position in the network on the opinion formation process and thus on the epidemic, we consider several strategies for the initial assignment of the pro-opinions.

1. *hubs*: The supporters are assigned to hubs—vertices with the highest degree.
2. *betweenness*: The betweenness centralities of the nodes underlay the probability distribution, from which the vertices are drawn. The higher the value, the more likely a vertex will be chosen.
3. *high-degree*: Pro-opinions are assigned with respect to the degree distribution of the vertices. Again, the higher the value, the more likely a vertex will be chosen.
4. *random*: The vertices are selected uniformly at random from the entire population.
5. *hub-community*: A heuristic community search. Initially, the supporter set is filled with a vertex with the highest degree along with its neighbors. Next, repeatedly as long as there are places for pro-opinions available, new vertices are added to the supporter set. These are neighbors of a supporter that has not been considered yet and that has the highest degree with respect to the entire opinion layer.
6. *low-degree*: The least connected vertices are among the candidates for vaccination supporters. Pro-opinions are assigned with respect to the degree distribution of the vertices. The lower the value, the higher probability to be chosen.
7. *hub-neighbors*: The candidates are adjacent to but not themselves hubs.
8. *mod-community*: The supporters are members of communities calculated using Clauset-Newman-Moore greedy modularity maximization algorithm.[1] The communities are sorted by the number of members and taken one by one as long as the number of available supporters is not exhausted.

[1] This method is designed to find communities in, among others, scale-free networks.

9. *coworkers*: The pro-opinion is assigned to vertices that build a connected rectangular shaped sub-grid on the disease layer.

Once the pro-opinions are assigned, the opponents are chosen randomly from the remaining nodes, and all others are set to neutral. Which strategy is used in the simulation is set in the parameter $\mathcal{O}_s$.

After the initialization, while the opinion formation process unfolds, the view of a selected individual is updated according to one of the following four adoption methods. The individual assumes the opinion of a randomly chosen neighbor (*random*) or of the majority of the neighbors (*max*) or indicated by the sign of the sum of the opinions of the neighbors (*sum*) or the closest to the average of the neighboring opinions (*mean*). Which method is used in the simulation is specified by the parameter $\mathcal{O}_a$. It is possible to apply all methods by randomly choosing one at each iteration step. As a matter of fact, accepting the contrary opinion does not usually come easy. Therefore the parameter ρ represents the probability that the calculated opposite opinion will ultimately be accepted.

2.2 The Disease Layer

The epidemic dissemination process we consider on the disease layer is based on the Susceptible-Infected-Recovered (SIR) model extended by the state of immunization [16,28]. Individuals who consent to the vaccination, in particular the initial supporters in the opinion layer, enter the epidemic simulation in the immunized state. An infection begins in a predefined number of individuals in the population—given by the parameter ι—who, of course, are not vaccinated. Once the simulation is triggered and it is the turn of the disease layer, the state of the individual being considered is updated according to one of the following rules. A susceptible supporter is vaccinated without restrictions whereas a susceptible neutral with a predefined very low probability η. If not eligible for immunization, a susceptible can get infected provided there are infections in the direct neighborhood. As a matter of fact, the more infected neighbors the higher risk of infection. For that, the parameter β that represents the probability of getting infected, increases by the percentage of the infections in the neighborhood: $\beta\left(1+\frac{I_u}{N_u}\right)$, where N_u is the number of all neighbors of the considered susceptible u and I_u is the number of the infected. An infected individual recovers with a predefined probability γ. A vaccinated or recovered one remains in the assumed state till the end of the simulation. At one iteration, an individual may record exactly one state.

To give an impression of how the process on the opinion layer influences the disease spread, we show the results of one simulation run initialized with the default values as given Table 1. In Fig. 2, the curves capture the two simultaneously started and alternately altered processes on the opinion layer (far left) and the disease layer (second from the left). Both plots on the right side display the epidemic spread launched in parallel with the same initial parameters as on the left side but with the disengaged opinion layer. Here, the individuals are

Table 1. Parameters controlling the simulation.

Layer	Par.	Def. value	Parameter definition
	ω	0.75	Probability of selection of the disease layer
	n	50	Range of the square lattice graph, n^2 is the number of nodes in each layer
	m	1	# edges to be attached from a new node in the Barabási-Albert graph
Opinion	υ^-	10%	Initial anti-opinions
	υ^+	10%	Initial pro-opinions
	$\mathcal{O}_s$	*rand*	Strategy to assign supporters
	$\mathcal{O}_a$	*all*	Opinion adoption method
	ρ	0.25	Probability that the contrary opinion is adopted
Disease	ι	1%	Initial infections
	β	0.95	Probability that a susceptible gets infected by infectious neighbors
	γ	0.25	Probability that an infected recovers
	η	0.02	Probability that a susceptible neutral gets vaccinated

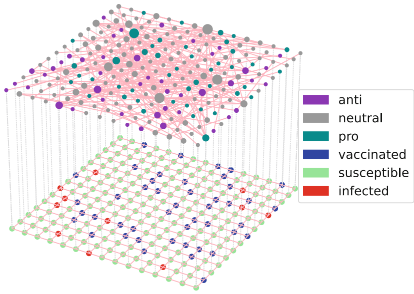

Fig. 1. An example of a multiplex with an opinion (top) and disease (bottom) layer initialized on a 15 × 15 - lattice and with respect to default values of parameters $m, \upsilon^-, \upsilon^+, \mathcal{O}_s$, and ι as displayed in Table 1.

vaccinated only in the initial phase (third from the left) or not at all (far right). To measure the extent of the epidemic and thus to compare different scenarios, we count all individuals who became infected within a simulation run. Considering the three disease courses in the given example, 58% of the population gets infected when the disease spread is decelerated by increasing vaccinations upon opinion formation, while 88% in the case of a fixed number of immunized individuals and 99% if no one is vaccinated at all.

3 Results

In our numerical experiments, we focus on exploring how the pro-opinions should be scattered on the opinion layer in order to achieve the most efficient diffusion of supporters' views in terms of flattening the infection curve on the disease layer. Thus we mainly concentrate on variation of the parameters that deploy the opinion layer: methods for the supporter placement and view adoption as well as the number of initial pro and anti-opinions.

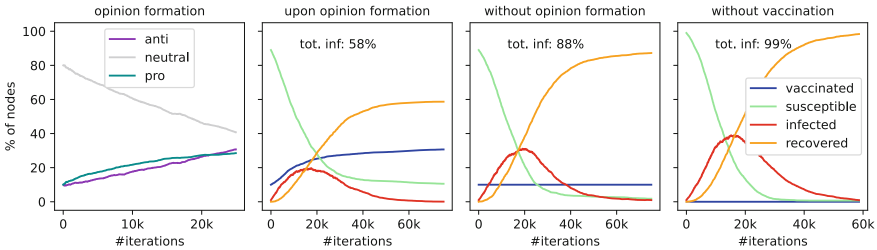

Fig. 2. An example of a disease spread course (second from the left) linked to an opinion formation process (far left) and thus affected by a growing rate of vaccination supporters, compared to the constant (third from the left) or absent rate of immunized individuals (far right). All other parameters are set to default.

3.1 Varying the Opinion Assignment and Adoption Method

In the first test scenario, we investigate the impact of the initial opinion assignment and the opinion adoption method applied to the opinion layer on the extent of the outbreak of the disease. To do this, we vary the parameters $\mathcal{O}_s$ and $\mathcal{O}_a$ and set all other to defaults given in Table 1. The results are displayed in Fig. 3. The boxplots compile percentage of the total number of infected individuals within a simulation. Per method of the initial assignment of the vaccine supporters, ordered on the x-axis, all four different adoption methods and its random mixing, distinguished by different colors, are considered.

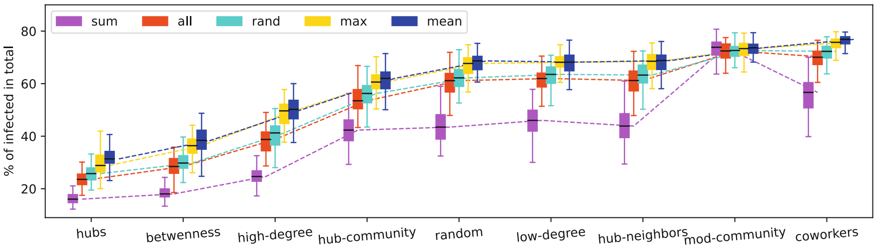

Fig. 3. Comparing the percentage of all infections while running 100 simulations per initial opinion assignment (x-axis) and adoption method (the color map in the legend).

According to the plot, both, the initial placement of the vaccine supporters on the opinion layer as well as the opinion adoption method decide on the extent of the epidemic. Hubs and generally vertices with the highest network centralities values are the most effective influencers. It may be well assumed that the potential number of nodes a supporter can influence plays a crucial role. The performance drops when the best connected nodes are stuck in a like-minded community, as the numbers for *hub-community* and *mod-community* show. In these cases, the results are close to and even worse than the fully random approach. A highly connected node may have only a few connections to like-minded neighbors so that there are enough candidates left to be persuaded. Such a pattern is certainly missing in the case of *coworkers*. Here, we notice that seeding a pro-opinion to a group of individuals connected physically, e. g. by a common working place, does not contribute to a fruitful transfer of views. The expectation that vertices of low-degree usually being simultaneously hub-neighbors would be able to affect the potent neighbors and transmit a spark that set off the entire network, turned out to be gratuitous.

Regarding the opinion adoption methods, the rank order of the colored boxplots per initial assignment method, x-tick, is the same except for *mod-community*. Taking the sign of the sum of the neighboring opinions, the purple color, appears to be the most efficient adoption method, followed by the random approach after a visible gap, and then *max* and *mean* close behind, both performing almost equally with a slender advantage of the majority approach. The outstanding case *mod-community* confirms that in a closed like-minded community there is little room for an exchange or spread of opinions. Regardless of the adoption method the flow of information is limited.

3.2 Varying the Initial Number of Pro and Anti-opinions

Beside the selection of the supporters of the pro-vaccine opinion, it is the number of supporters and opponents present when the epidemic breaks out that shapes the infection curve. In the following test scenario we vary the parameters υ^+ and υ^- which stand for the percentage of the pro and anti-opinions that are assigned on the opinion layer at the beginning of a simulation. All other parameters remain fixed to defaults as given in Table 1 and every simulation begins with a generation of a new pair of graphs the layers are based on. The results are shown in Fig. 4. In the outer frame of the chart, a boxplot corresponds to a pair (υ^-, υ^+) being an element of the cross product on the set $\{5, 20, 15, 20, 25\}\%$ and arranged along the x-axis. On the y-axis, we have the percentage of infected individuals in total. The boxplots form a noticeably regular pattern. For a fixed υ^+ and increasing υ^-, the number of total infections ascend, predictably. The growth is moderate and close to linear with the smallest slop when $\upsilon^+ = 25\%$, and it generally gets flatter the lower the y-value, except for the group of $\upsilon^+ = 5\%$ in the lower chart. On the other side, the boxplots for a fixed υ^- and increasing υ^+ form a steep descent.

A similar pattern can be assumed for higher rates. Hence for the values 30% to 50%, again with a 5% step, only the cases when $\upsilon^+ = \upsilon^-$ are considered and the results shown in the inner frame. As one reads from the plot, from 30% on minor disease outbreaks can be observed and they practically vanish by 50%, regardless of the initial placement of the pro-vaccine individuals. For comparison, we mark the outcome of the epidemic when both υ^+ and υ^- are set to zero, i. e. the opinion layer is disabled and thus no vaccination takes place on the disease layer. In this case, close to 90% of the population gets infected. As

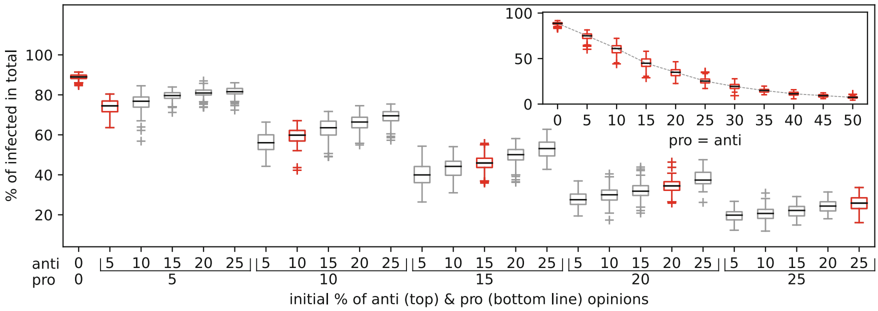

Fig. 4. Comparing the percentage of all infections when varying υ^+ and υ^-, with $\mathcal{O}_s$ set to *random*. Each boxplot compiles results from 100 simulations.

we determined in further tests, the arrangement of the boxplots as exposed in Fig. 4 is independent from the initial pro-opinion seed $\mathcal{O}_s$.

3.3 Extending the Lattice

The experiments discussed so far were carried out on a fixed population size of 2500 individuals. Figure 5 gives an insight into how sensitively our simulation reacts to the growing number of participants. Beginning with the default 50×50 lattice, the remaining ticks on the x-axis correspond to 10,000, 22,500, 40,000 and 62,500 number of nodes on each layer. To assess the impact of the initial supporter assignment in this test scenario, we consider a selection of three $\mathcal{O}_s$-methods: *high-degree*, *random*, and *coworkers*; each of them belongs to one of the three distinguishable y-value ranges in Fig. 3. Each boxplot compiles results of 10 simulations. As the number of nodes in the layers increases, the infection rates decrease and become less volatile, as shown in the left plot. The trend towards a lower infection rate as the network grows is maintained with every initial setting of the opinion layer. The relative position between the boxplots of different colors, i.e. corresponding to different $\mathcal{O}_s$-methods remains preserved. For each graph size, *high-degree* performs best, followed by *random* and then *coworkers*. Again, we observe the robustness of the simulation with regard to the initial pro-opinion assignment. It is to be expected that the relative position of the boxplots obtained for different $\mathcal{O}_s$-methods as well as (υ^-, υ^+)-pairs will lean on the patterns formed in Figs. 3 and 4 respectively.

According to the right plot in Fig. 5, the simulation times[2] grow steadily, approximately quadratic in the number of nodes. Starting with about one minute for a 50×50-lattice and reaching to over three hours on 250×250. The computation time is, however, less sensitive to the parameter $\mathcal{O}_s$. Generally and intuitively, the less infections in total the sooner an epidemic is over.

[2] The computations were conducted on 3.2 GHz 16-Core Intel Xeon W with Turbo Boost up to 4.4 GHz and 768 GB RAM.

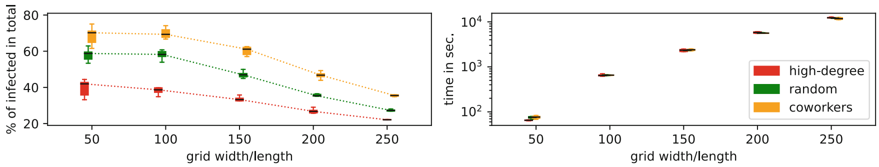

Fig. 5. Comparing the percentage of all infections (left) and the running times of the simulations (right) when increasing the number of nodes in the layers. Each boxplot compiles 10 simulations.

It should be mentioned that according to additional tests, our simulation is not sensitive to the density of the network where the disease spreads.

3.4 Further Remarks

Our scope is to observe how the dynamic process on the opinion layer influences the epidemic spread. Therefore, in our tests, we focused on varying the parameters controlling the opinion layer by keeping fixed the remaining parameters. In our tests, we assume that a disease spread process is more dynamic than the exchange and acceptance of views and thus set $\omega = 0.75$. The default values assigned to ι, η, β and γ were chosen intuitively with a reliable disease spread course on a lattice in mind. The values $\iota = 1\%$ and $\beta = 0.95$ ensure that the infection circulates despite sparse connections between the individuals. Considering the SIR model, we assume that individuals who recover from the infection become immune and thus they are not in need for a vaccination. The remaining parameters ρ and η are similarly of negligible importance. Summing up, varying the values of any of the parameters mentioned in this paragraph leads to a slightly different shape of the infection curve. However, the impact of the opinion layer on the disease spread is noticeable in any case and we assume it is analogous to the results presented above.

4 Conclusions

We presented an approach of coupling an opinion formation with a diffusion process. For this we consider a multiplex social network consisting of two layers spanned on the same set of individuals. Both processes are initially started independently on a different layer, but influence each other as they progress. The opinion formation process bases on vaccine sentiments and the diffusion process is an epidemic spread. Our main concern was to observe how the spread of the disease is sensitive to individuals' immunization readiness. As one would expect, the selection of the pro-opinion seed determines the extent of the epidemic outbreak. The notable choice are individuals with a central position in the opinion layer. What is striking, however, that individuals related through employment—referred to as neighbors on the lattice—poorly exchange their views. Comparing opinion adoption methods, we made another remarkable observation that taking the signum of neighboring opinions leads to a superior influence of the supporters. Regardless of the technical setting of the considered multiplex and its layers, our simulation shows that a social contagion such as epidemic spread is conditioned by the population's views on the immunization. It points out that spreading a positive attitude towards vaccination is a powerful tool in the fight against the virus and encourages further reflection of complex systems of this kind. The approach from the multiplexity, which we pursued in this contribution, allows investigating a coupling of two dynamic processes in an equalized complexity.

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