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IMPACT OF VACCINATION OPINION DYNAMICS ON INFLUENZA EPIDEMICS

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The aim of this study is to test the hypothesis that the dynamics of social opinion about vaccination influence the development of the epidemic process, using an influenza epidemic as an example. It is assumed that the opinion dynamics is completed before the start of the seasonal influenza outbreak, by which time everyone has made a decision about vaccination. Such decisions influence the formation of personal immune status for each economic agent as well as the formation of collective immunity in the population as a whole. The epidemic process is studied using two modifications of compartmental models (SIR and SEIRD). The cost-effectiveness of vaccination is also studied. The modeling is accompanied by a simulation of opinion dynamics and the epidemic process, implemented on a network model based on a random graph. A scenario analysis is performed based on statistical data on influenza incidence and annual vaccination campaigns in Russia.

Keywords: vaccination; influenza epidemic; network model; opinion dynamics; compartmental models.

Introduction

Throughout history, humanity has faced epidemics that threaten lives and disrupt economic activity, and in recent decades large outbreaks have become more frequent due to high population density, limited healthcare access, mobility, and climate change [1, 2]. Vaccination is a key tool: it builds population immunity. In addition, recently it has significantly reduced measles, mitigated seasonal influenza, and reduced hospitalizations and deaths from COVID-19 [3 – 6]. Despite these benefits, public attitudes toward vaccination are highly polarized: debates in private and public spheres, especially during COVID-19 campaigns, have sharpened the divide between vaxxers and anti-vaxxers, while the undecided majority ultimately determines the achieved level of protection [6, 7].

We hypothesize that epidemic dynamics are linked to the preceding vaccination campaign, which effectiveness depends on opinion dynamics in a heterogeneous society, so the system has many possible outcomes and no established regularities. Given the complexity and approximative nature of epidemic models, this hypothesis must be explored by simulating scenarios. We focus on influenza because it is one of the world's most common and dangerous infections, with frequent, large, and deadly epidemics and pandemics. In addition many effective vaccines and extensive international statistics on seasonal outbreaks and vaccination are available [1 – 6].

For emerging pandemics of new diseases, choosing countermeasures is difficult, and mathematical models help predict epidemic trajectories but require many assumptions. Our work extends earlier models by assuming two opposing attitude groups and a pool of undecided individuals influenced by others. We model opinion dynamics up to the start of seasonal epidemic, after which each individual has chosen to vaccinate or not. This assumption is done according to world practice: it is customary to complete flu vaccination before the outbreak begins.

Following earlier studies on modeling the epidemic spread of malaria [8], COVID-19 [6, 9], influenza [10, 11], and other infections [12], and the subsequent outbreak is described by a modification of the classical Kermack–McKendrick compartmental model [13] (SIR and SEIRD variants). The aim is to test how opinion dynamics affect epidemic development. The issue of how a vaccination campaign can affect the efficiency of social activities and reduce economic losses related to an increase in illness is also being explored. Therefore, in the context of our study, decision-makers are considered not as individuals, but as economic agents.

The article is organized as follows: Section 1 introduces the problem; Section 2 studies attitudes toward vaccination and builds the opinion dynamics model with scenario analysis; Section 3 presents epidemic modeling with SIR and SEIRD modifications; Section 4 summarises the results.

1. Social Attitudes to Vaccination and Opinion Dynamics

As it has already been mentioned, society is extremely divided on the question of vaccination [7]. Some people reject vaccination for personal, philosophical, psychological, ethical or religious reasons, often citing safety, efficacy or ethical concerns, past negative experiences, or a preference for "natural" immunity; such people are commonly called **anti-vaxxers** and may be linked to movements spreading misinformation about vaccines. Others, the **vaxxers**, support vaccination as a key public health measure, point to robust evidence of safety and effectiveness in preventing or mitigating serious diseases, accept that vaccines are not 100% effective, but judge that benefits outweigh risks and often support mandatory vaccination in settings like schools or healthcare.

Anti-vaxxer views are typically associated with distrust of authorities and the medical establishment, whereas vaxxers tend to support scientific consensus and public health policy. Between these poles there is a third group: doubters who have not formed a definite attitude. How their opinions evolve determines the eventual vaccination coverage at the onset of an epidemic and is itself a complex opinion-dynamics process. The main advantages of vaccination include herd immunity (reduced transmission when coverage is high), protection of vulnerable groups (children, elderly, immunocompromised), possible reduction of virulence, and socioeconomic benefits such as lower healthcare burden and costs.

Thus, we treat choosing vaccination as a conscious decision to reduce risk, both from a biomedical and socio-economic point of view. Similarly to risk attitudes in risk management (risk-seeking, risk-neutral, risk-averse), we divide society into strong opponents (anti-vaxxers), undecided individuals (doubters), and supporters (vaxxers), and then study how the first and third groups influence the opinion formation of the middle group.

1.1. Opinion Dynamics in the Network

We make several assumptions to clarify the problem. First, we study bounded communities such as one office, one school class or one kindergarten group, and thus in simulations use populations of 30, 50, and 100 agents. Second, following earlier work [10, 11], we model opinion dynamics as a Markov process on a network and interpret stabilization as reaching consensus in the sense of De Groot [14]. In this network there are n decision makers of three types: anti-vaxxers, vaccination supporters, and doubters, all analyzing the available information.

To initialize attitudes, we use empirical psychological data on risk propensity (as in [10, 11]): risk-seekers are 18%, risk-neutral are 65%, risk-averse are 17%. This motivates an initial split of the economic agents: 17% of vaxxers, 65% of decision makers (doubters), 18% of anti-vaxxers. The population is represented as a network $G = (N, P)$, where N is the set of agents, and P is a stochastic matrix of connections $p_{ij},\ i, j = 1, \ldots, N$. We consider several structures and conclude that random sparse and random connected graphs are most suitable for modeling of the considered relationship in limited teams.

Initially, each agent i is characterized by her/his type (anti-vaxxer, vaxxer, doubter) and her/his belief f_i^0 (vaccinate / not vaccinate). Anti-vaxxers fix $f_i^0 = 0$ and never change its value, vaxxers fix $f_i^0 = 1$, while doubters' initial beliefs are drawn from a normal distribution with chosen parameters, under different patterns of how the three types are placed on the network. Information exchange follows a Markov-type updating with trust weights [15]: at each iteration, $f_i^t = \sum_{j=1}^N p_{ij} f_j^{t-1}$. Interactions continue up to 10^3 iterations or until time T when, for all i $\sum_{t=1}^T (f_i^t - f_i^{t-1})^2 < 10^{-3}$. After convergence, each agent's final strategy (vaccinate / not vaccinate) is fixed: anti-vaxxers remain unvaccinated, vaxxers remain vaccinated, and only doubters decide based on a critical threshold on their final estimate (vaccinate if it is above the threshold).

1.2. Numerical Simulation of Opinion Dynamics

The results of this part of the numerical simulation were analysed in detail in [10], here we only summarise them briefly. To study the dynamics of opinions on vaccination in the network, we performed repeated simulations using the algorithm described above, implemented in Python on the Jupyter Notebook platform.

Each agent is represented by a node with the following characteristics:

- the propensity to vaccinate, visualised as the shape of the node: positive attitude (vaxxers) – triangles, neutral (doubters) – squares, negative attitude (anti-vaxxers) – circles;

- the current decision of the agents to vaccinate is represented by the colour of the node: decided to vaccinate – light gray; decided not to vaccinate – black.

Here are just a few examples from the study [10, 11] illustrating different scenarios of opinion dynamics in a population represented by networks of different configurations.

Example 1. In this example we consider the network consisting of 30 nodes and having the modification of the random sparse graph. The distribution of initial attitudes towards vaccination is as follows: negative attitudes are represented by 5 nodes, positive attitudes by 5 nodes, neutral attitudes by 20 nodes. Initially, there are 14 people in the network who are going to vaccinate and 16 who are not.

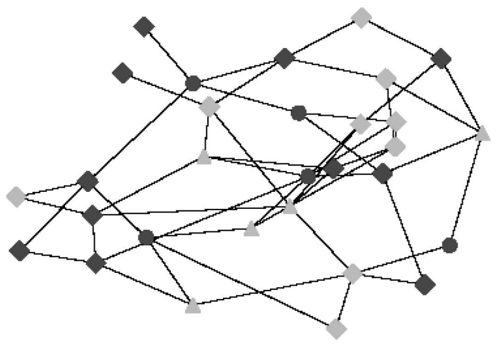

Fig. 1. Initial state of population, before opinion dynamics

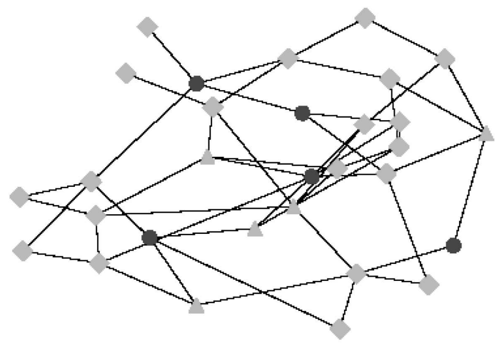

Fig. 2. The result of opinion dynamics: final state of population after the third iteration

If we compare the initial state of the population and the resulting state (Fig. 1 and Fig. 2), we understand that here is a case of dynamics that is positive in the following meaning: the number of vaccinated increases and becomes greater than the number of those who do not vaccinate. Among the possible reasons for this effect, we can mention the large number of agents with a neutral attitude in the initial state of the network and the location of such agents: they are located throughout the network with a large number of connections. Moreover, the fact that the first agent to change her/his opinion had a positive attitude also has an impact on the dynamics: in the similar case with another type of agent in this position, we got a different scenario. The final result of this dynamics is the state where only people with initially negative attitudes do not vaccinate.

Example 2. In this example, we simulate the process under study in a randomly connected graph with 30 nodes. The distribution we analyze is as follows: 8 nodes with a negative attitude, 3 nodes – with a positive attitude and 19 – with a neutral attitude. Among these, there are 15 who will vaccinate first and 15 who will not vaccinate.

In this example, we are faced with a "negative" dynamic: the number of agents who will vaccinate increases in the end, but not significantly (only one is added). If we analyze this fact, we will find the following reasons: agents with different predispositions are very mixed in the network; at the same time, the agents with a negative attitude have a large number of connections. Taking these facts into account, we can formulate that in such examples there is no effect of opinion dynamics. The final state of the system is not very different from the initial one.

We examined various opinion dynamics scenarios beyond the examples above, repeating simulations across network modifications, node attitude assignments (positive, negative, neutral), and initial vaccination intention shares. In summary, network opinion dynamics range from extremely negative to positive, depending on network type, inter-attitude links, initial spatial mixing, group proportions, and early influencers' vaccination propensity.

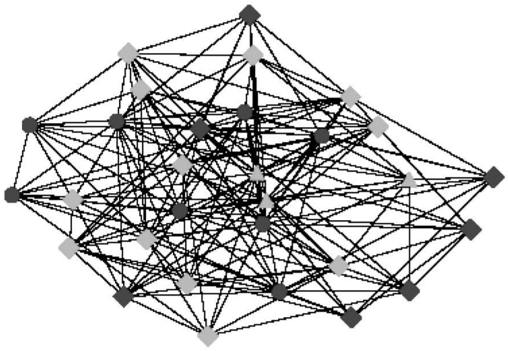

Fig. 3. Initial state of population, before opinion dynamics

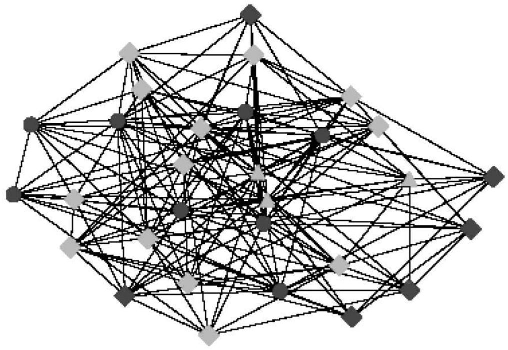

Fig. 4. The result opinion dynamics: final state of population after the second iteration

2. Epidemic Process Model

In this section we briefly review two compartmental epidemiological models, modified SIR and SEIRD, assuming that opinion dynamics have already finished and agents have decided on vaccination before the seasonal epidemic rise. This assumption helps to make the model more realistic, as in real-world practice, flu vaccinations are usually completed before an epidemic outbreak. From a medical perspective, vaccinating during the epidemics is not only considered ineffective, but also has the potential to harm an individual's immune system and health.

Previously, we analysed isolated bounded groups, but since an epidemic affects the whole society, we aggregate these groups into a single population, with sub-populations represented by networks of different configurations. In the compartmental setting [10, 11] we also assume that recovery and mortality rates, as well as infectivity (virulence), remain constant throughout the seasonal epidemic period.

2.1. SIR Modeling Application

We assume that the seasonal epidemic rise can be described by a SIR-like model [10]. Let us introduce the following notations. Let H be the total number of agents in the population (the cardinality of the specified subpopulation association), P^+ be the number of vaccinated, P^- be the number of unvaccinated, I be the number of infected, R be the number of recovered. P^+, P^-, I, R are the dynamic functions.

Now we can apply the classical SIR model [13] in epidemic modeling, following the studies described in works [8 – 13]. In our setting, the function S – susceptible – actually decomposes into two: vaccinated P^+ and unvaccinated P^-. According to these settings, the epidemic process can be described by the following system of equations:

$$\begin{cases} \dot{P}^+ = -\beta_2\, P^+\, I - \beta_5\, P^+, \\ \dot{P}^- = -\beta_4\, P^-\, I, \\ \dot{I} = \beta_2\, P^+\, I + \beta_4\, P^-\, I - \gamma I, \\ \dot{R} = \beta_5\, P^+ + \gamma I. \end{cases} \tag{1}$$

The parameters β_2, β_4, β_5 and γ have their epidemic meaning. γ is the recovery rate: $\gamma = 1/T_b$, where T_b is a characteristic duration of illness; for the vast majority of influenza strains it is assumed to be $T_b = 15$ days [1, 2]. Together with T_b, let's consider the parameter T, which is the duration of the seasonal increase ($T = 100$ days). The parameters β_2, β_4 and β_5 are defined below in the text.

There must be a "patient zero" (at least one infected person in the population) for an epidemic to begin. Mathematically, this condition means that at the initial time moment $I(0) = 1$ and $R(0) = H - P^+(0) - P^-(0) - I(0)$. Along with the initial conditions, we should take into account the epidemic start conditions:

$$\beta_2\, P^+(0)\, I(0) + \beta_4\, P^-(0)\, I(0) - \gamma\, I(0) > 0.$$

Two basic goals of such research are to find the values of the number L^+ of recovered patients among the vaccinated and the number L^- of recovered patients among those unvaccinated:

$$L^+ = \int_0^\tau \beta_2 \, P^+ \, I \, dt, \qquad L^- = \int_0^\tau \beta_4 \, P^- \, I \, dt, \tag{2}$$

where τ is length of intervals by days; it can take values $\{30, 60, 90, 100\}$.

2.2. SEIRD Modeling Application

Using the SIR model to model the epidemic process, we assumed that seasonal influenza epidemics in civilized countries have been accompanied by relatively low mortality in recent decades [1, 2]. However, if we stop ignoring the proportion D of deaths due to complications of the virus and also include the presence of latent virus carriers E for a period of time (or, exposed), we arrive at the need to apply another modification of the compartmental model, the SEIRD model [11].

In addition to the dynamic variables used in the SIR model (P^+, P^-, I and R), we introduce the following notations: let E be the number of those in whom the disease is in the incubation period (exposed (latent)), D be the number of deaths.

Now we can formulate a model based on the classical SEIRD scheme [16], similar to what was done in [11]. According to these results, the epidemic process for the model under consideration can be described by the following system of equations:

$$\begin{cases} \dot{P}^+ = -(\beta_1 + \beta_2) \, P^+ \, I - \beta_5 \, P^+, \\ \dot{P}^- = -(\beta_3 + \beta_4) \, P^- \, I, \\ \dot{E} = \beta_1 \, P^+ \, I + \beta_3 \, P^- \, I - \delta \, E, \\ \dot{I} = \beta_2 \, P^+ \, I + \beta_4 \, P^- \, I + \delta \, E - \gamma \, I - \mu \, I, \\ \dot{R} = \beta_5 \, P^+ + \gamma I, \\ \dot{D} = \mu \, I, \end{cases} \tag{3}$$

where β_i, $i = \overline{1, 5}$, δ, γ and μ are the parameters of the model.

Let's describe these parameters in more detail. Coefficients β_1 and β_2 are the rates of transmission in the cases of contact of P^+ with an exposed (latent) or infected correspondingly; β_3 and β_4 are the rates of transmission in the cases of contact with an exposed or infected correspondingly for P^-; β_5 is the rate of transmission from susceptible vaccinees transition into immunized (recovered); γ is the rate of recovery: $\gamma = \frac{1}{T_1}$, where T_1 is average duration of illness; δ is the rate of transition from exposed to infected: $\delta = \frac{1}{T_2}$, where T_2 is average latency period; μ is the mortality rate; T is the duration of one seasonal rise in the incidence of disease.

System (3) must be accompanied by initial conditions. The number of vaccinated $P^+(0)$ and the number of unvaccinated $P^-(0)$ are defined as the results of opinion dynamics for each experiment. All other system variables prior to the onset of an epidemic outbreak: $E(0) = 0$ (it is assumed that there are no latents in the system), $I(0) = 1$ ("patient zero" condition), $R(0) = 0$, $D(0) = 0$. Suppose that an agent from the unvaccinated group has infected the system. Then the number of unvaccinated $P^-(0)$ are $(P^-(0) - I(0))$. The average duration of illness is $T_b = 15$ days, therefore, $\gamma = 1/15$; average latency period is $T_2 = 5$ day, therefore, $\delta = 0.2$; mortality rate μ is 0.001; the duration of one seasonal rise is $T = 100$ days.

Along with the solution of the system (3) we will search the values of the number L^+ of people who were vaccinated and got sick:

$$L^+ = \int_0^\tau ((\beta_1 + \beta_2) \, P^+ \, I) \, dt, \tag{4}$$

and the number L^- of people who were not vaccinated and got sick:

$$L^- = \int_0^\tau ((\beta_3 \, + \beta_4) \, P^- \, I) \, dt, \tag{5}$$

where τ is, as before, the length of the interval in days; it can take the values $\{30, 60, 90, 100\}$.

2.3. Assessing the Cost-Effectiveness of Vaccination

In order to estimate the cost-effectiveness of vaccine prophylaxis [5], we must account for several features of the model and introduce simplifying assumptions. Following the results of [17], we now adapt them to our setting.

First, maximising economic efficiency is equivalent to minimising total losses U due to increased morbidity. These losses include treatment costs, temporary replacement of ill workers, full replacement in the event of fatalities, and the fixed (time-independent) cost of the vaccination campaign.

Second, to make U tractable, we ignore differentiation by wage levels (using a minimum wage), age groups (children, pensioners, working-age), disease severity, and corresponding treatment cost variation. Acknowledging that this simplifies and coarsens the loss estimates, we partially compensate by averaging the parameter values: h (mean cost of influenza treatment), s (mean cost of wage replacement), and v (mean cost of a vaccine).

Taking all the above into account, let us construct the loss functional for the case of the SIR model

$$U_{SIR} = \int_0^{\tau} \left(\beta_2\, P^+ + \beta_4\, P^-(t)\right)\, I(t)(h+s)\, dt + P^+(0)v, \tag{6}$$

where the first summand is responsible for the cost of treatment and replacement of work due to temporary disability and the second summand is responsible for the cost of the vaccination.

For the case of the SEIRD model, the functional will take the form

$$\begin{aligned} U_{SEIRD} = \textstyle\int_0^{\tau} \left((\beta_1+\beta_2)\, P^+ + (\beta_3+\beta_4)\, P^-(t)\right)\, I(t)(h+s)\, dt +& \\ +D(T)\, s + P^+(0)v,& \end{aligned} \tag{7}$$

where, similarly to the previous case, the first summand is responsible for the cost of payment for treatment and replacement, the second for replacement due to death and the third for the cost of vaccination.

In numerical modeling, instead of the parameters h, s, and v, we used the values obtained according to the official statistics of the cost of vaccination, treatment, and minimum wage in the city of St. Petersburg, based on data from [2] and [18].

2.4. Numerical Simulation of the Epidemic Process

To demonstrate how epidemic dynamics depends on the outcome of the previous modeling step (opinion dynamics), we simulated many different scenarios, including the most pessimistic cases, the most optimistic and neutral ones. In this paper we present in detail only one corresponding to the neutral (the most average) case.

We study three groups of 5000 people each: a group with a negative result of opinion dynamics (the majority chooses not to vaccinate), a group with a positive result (the majority chooses to vaccinate), and a neutral group (initially about half plan to vaccinate, but after opinion exchange the majority vaccinate).

Using a Python implementation on the Jupyter Notebook platform, we ran a series of repeated simulations; one representative run is described below. We assume that vaccinated individuals are less likely to become ill but may enter a latent stage, and that many vaccinated acquire post-vaccination immunity, moving directly to recovery. Unvaccinated individuals have a higher probability of becoming ill and also a relatively high chance of entering the latent state. Initially, there are no latent cases $E(0) = 0$, and a single "patient zero" $I(0) = 1$.

These assumptions are reflected in the initial conditions and parameters: the transmission rate for contacts involving unvaccinated exposed and infected individuals is much higher than for vaccinated ($\beta_1 \gg \beta_2$, $\beta_5 > \beta_1$, $\beta_4 > \beta_2$). The program produces experimental trajectories for the groups P^+ (black solid line), P^- (black dashed line), I (black dash-dot line), R (black dotted line), E (gray dashed line), and D (light gray dotted line).

Example 3. In the figure 5 an illustration of the case of the "neutral scenario" can be seen: the number of those who are going to vaccinate is almost the same as the number of those who is not going to vaccinate: 2466 and 2534. After opinion dynamics their numbers changed to 3769 and 1231 correspondingly.

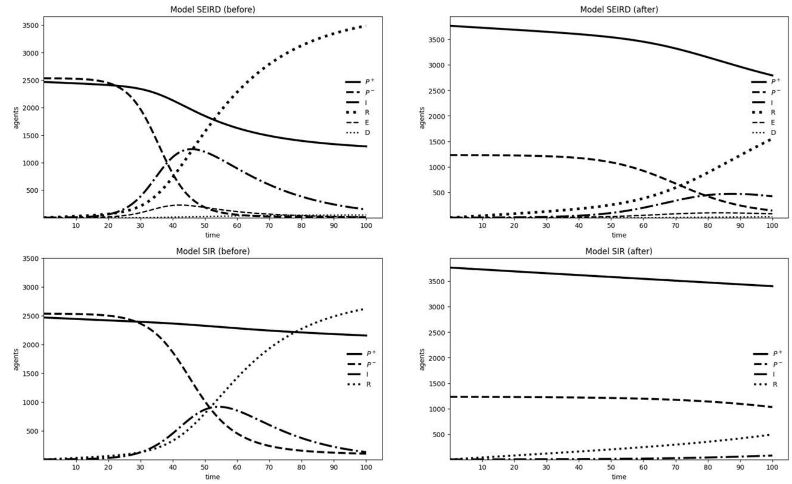

Fig. 5. Epidemic process in the group with neutral scenario

In this example L^+ decreased from $39,82\%$ to 16.72% for SEIRD (from $3,31\%$ to $0,18\%$ for SIR), and L^- also decreased from $99,70\%$ to $88,53\%$ for SEIRD (from $95,98\%$ to $16,33\%$ for SIR). The peak shifts down to 468 from 1245 and to the right to 87,5 from 46 for SEIRD (down to 77 from 915 and to the right to almost 100 days from 54 for SIR). Economic costs illustrated the following changes: for the SIR model, they declined from $U_{SIR}^{before} = 87,157,830,29$ to $U_{SIR}^{after} = 8,517,452,85$, for SEIRD – from $U_{SEIRD}^{before} = 122,490,992,60$ to $U_{SEIRD}^{after} = 60,604,948,60$.

Interpretation of the experiment shows that in this case vaccination gives an economic benefit of 10 times in the model without taking the latents into account. Including the exposed into consideration also gives a good economic effect, reducing the economic cost of the system by more than a factor of 2. We have presented the results of only one experiment. Summarizing the results of the total series of experiments, the following conclusions can be drawn.

The number of people who become ill does not exceed 17% of all vaccinated, while among the unvaccinated it exceeds 90%. In all three groups, the maximum number of infected individuals decreases after the opinion dynamics and the redistribution of neutrals.

With parameters chosen according to the epidemic logic, the share of infected vaccinated L^+ in all groups and experiments does not exceed 45%, whereas for the unvaccinated L^- it reaches $88-100\%$. Under the influence of opinion dynamics, the morbidity peak $I_{\max}$ shifts to the right (the time $t_{\max}$ increases), and mortality decreases in all considered scenarios. In the framework of these initial assumptions, the vaccination campaign yields a positive effect, and opinion dynamics additionally reduce economic losses as vaccination coverage grows. Based on the results obtained, we would like to recommend that government bodies at different levels (municipal, regional, and federal) focus on promoting vaccination and vaccine prevention as much as possible for all segments of the population.

Conclusions

The study considers a population heterogeneous in vaccination attitudes: anti-vaxxers, who emphasise safety, efficacy and ethical concerns and often rely on unscientific or poorly substantiated sources, and vaxxers, who stress public health benefits and refer to scientific evidence and expert recommendations. Repeated simulations of opinion dynamics on networks showed that both "positive" and "negative" scenarios are possible, with the final balance between those choosing vaccination and refusal depending on network type, connectivity, spatial mixing of attitudes, initial fractions of each group, and which agents begin spreading opinions first.

Empirical material indicates that, although vaccines are not perfect, their public health benefits greatly exceed their risks, and that vaccination—here analyzed via influenza data—can be viewed both as personal risk management and as a factor of overall economic efficiency; in principle the models can be adapted to other infections (malaria, Ebola, COVID-19). The study tests the hypothesis that the vaccinated/unvaccinated ratio produced by prior opinion dynamics affects subsequent epidemic development. Using SIR and SEIRD compartmental models to simulate influenza seasonality, it finds that a "positive" opinion scenario in closed communities (offices, classes, kindergarten groups, etc.) increases pre-season vaccination coverage, reduces total infections, delays the epidemic peak, and thereby improves societal economic efficiency.

Accordingly, government bodies at different levels (municipal, regional, and federal) need to take measures to increase the number of people who are vaccinated among doubters. These measures could include promoting vaccination in various ways, such as through social advertising or educational talks by doctors. It is also important to make vaccination as accessible as possible for all segments of society, including children in kindergartens and schools, students in universities, employees in different organizations, and pensioners at polyclinics and additional vaccination centers.

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ВЛИЯНИЕ ДИНАМИКИ МНЕНИЙ О ВАКЦИНАЦИИ НА ЭПИДЕМИИ ГРИППА

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Целью данного исследования является проверка гипотезы о том, что динамика общественного мнения о вакцинации влияет на развитие эпидемического процесса, на примере эпидемии гриппа. Предполагается, что динамика общественного мнения завершается до начала сезонной вспышки гриппа, и к этому времени все уже принимают решение о вакцинации. Такие решения влияют на формирование индивидуального иммунного статуса каждого экономического агента, а также на формирование коллективного иммунитета у населения в целом. Эпидемический процесс изучается с использованием двух модификаций компартментных моделей (SIR и SEIRD). Также изучается экономическая эффективность вакцинации. Моделирование сопровождается имитацией динамик общественного мнения и эпидемического процесса, реализованной на сетевой модели, основанной на случайном графе. Сценарный анализ проводится на основе статистических данных о заболеваемости гриппом и ежегодных прививочных кампаниях в России.

Ключевые слова: вакцинация; эпидемия гриппа; сетевая модель; динамика общественного мнения; компартментные модели.

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