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Research Report

The effect of competition between health opinions on epidemic dynamics

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Abstract

Past major epidemic events showed that when an infectious disease is perceived to cause severe health outcomes, individuals modify health behavior affecting epidemic dynamics. To investigate the effect of this feedback relationship on epidemic dynamics, we developed a compartmental model that couples a disease spread framework with competition of two mutually exclusive health opinions (health-positive and health-neutral) associated with different health behaviors. The model is based on the assumption that individuals switch health opinions as a result of exposure to opinions of others through interpersonal communications. To model opinion switch rates, we considered a family of functions and identified the ones that allow health opinions to coexist. Finally, the model includes assortative mixing by opinions. In the disease-free population, either the opinions cannot coexist and one of them is always dominating (mono-opinion equilibrium) or there is at least one stable coexistence of opinions equilibrium. In the latter case, there is multistability between the coexistence equilibrium and the two mono-opinion equilibria. When two opinions coexist, it depends on their distribution whether the infection can invade. If presence of the infection leads to increased switching to a health-positive opinion, the epidemic burden becomes smaller than indicated by the basic reproduction number. Additionally, a feedback between epidemic dynamics and health opinion dynamics may result in (sustained) oscillatory dynamics and a switch to a different stable opinion distribution. Our model captures feedback between spread of awareness through social interactions and infection dynamics and can serve as a basis for more elaborate individual-based models.

Keywords: health behavior, socio-epidemiological model, behavioral response, opinion dynamics, prophylactic behavior

Significance Statement:

Epidemics and opinions about protective behavior spread via social contacts and influence each other. Individuals change health-related behavior depending on their opinion of suitable practices during an outbreak. To understand the interplay of opinions and epidemic dynamics, we model the interaction between two opposing opinions and an evolving epidemic. Increasing incidence of infection leads to higher popularity of the health-protective opinion, reducing infection transmission. The tendency of persons with the same opinion to connect impacts epidemic and opinion spread. We identified thresholds for shifts from coexisting opinions to a health-protective opinion taking over the population and the infection going extinct. To reach this, moving through waves of increasing infection is necessary. These dynamics are important for designing public health interventions.

Introduction

The notion that the relationship between epidemic dynamics and reactive collective behavior plays an important role in the course of an outbreak of an infectious disease has been recognized in theoretical epidemiology (1–5). This notion is supported by data collected during various outbreaks of infectious diseases, dating back as far as the Spanish flu pandemic of 1918 (1, 3, 5) to SARS pandemic (6, 7) and swine flu pandemic (8), and ending with the ongoing SARS-CoV2 pandemic (9). In total, two types of societal reactions to an infectious disease outbreak can be distinguished, namely, centralized top-down and individual-based bottom-up reactions. First, governing authorities may impose public health interventions aiming at protecting the most vulnerable groups, and mitigating the spread of infection. Typical measures are school closures, limitation of the number of persons in indoor spaces, and travel restrictions. Second, individuals may change their behavior by self-imposing protective measures such as hygiene measures or mask wearing in an effort to defend themselves from infection and its consequences (10). It has been observed that practicing of self-protective measures increased during outbreaks of infectious diseases and declined when the disease was eliminated (6–8). Thus, there is an indication for a feedback relationship between epidemic dynamics and uptake of self-protective measures.

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It was not until the 2000s that the importance of this type of reaction for epidemic dynamics was recognized and investigated using mathematical modeling (2, 4, 11). Accounting for the behavior–infection feedback relationships in epidemic models has helped to explain patterns observed in real world data. Multiple epidemic peaks and relatively small outbreaks, where much larger ones were expected, were convincingly shown to be the result of changes in individual human behavior during an epidemic (4, 5).

Health behaviors are a subject to (health) opinion held. The dynamics of circulation of ideas and beliefs in a population is studied in the field known as sociophysics. Even the simplest sociophysics models can have rich dynamics where a number of distinct opinion distributions is possible with a potential for bistability between them (12–14). To understand the effect of the feedback loop between disease spread and health opinion circulation on epidemic dynamics, it is important to understand the role of assumptions about the propagation of opinions on their distribution in the population. In this work, we consider the effect of interpersonal communications on the dynamics of health opinion competition using different functional representations for opinion switch rates. We show that depending on the shape of the functional response qualitatively different opinion distributions appear, which in turn affects outlook of an epidemic.

In the context of health-related opinions and the associated self-imposed preventive behaviors, pro- and antivaccination sentiments garnered a lot of attention (11, 15–18), while other investigations focused on nonpharmaceutical interventions such as mask wearing and social distancing (2, 4, 9, 19). While, ideally, vaccination is a nearly instantaneous event that protects an individual for a long time, the latter measures only confer protection while they are being practiced. For emerging infectious diseases for which pharmaceutical interventions are not available, as was the case with COVID-19 in 2020, the extent of the outbreak depends on the uptake rate of nonpharmaceutical measures by the population (20).

Health opinions can fall on a spectrum ranging from health-promoting, adaptors of which practice self-protective measures with the aim of protecting their health, to health-indifferent, whereupon individuals having such opinions do not modify their behavior. The health belief model (10) posits that adopting health-promoting measures is motivated by several constructs: (i) perceived susceptibility (risk of contracting a specific health problem), (ii) perceived severity (estimation of the consequences of this problem), (iii) perceived barriers (impediments for adopting a relevant health behavior), (iv) perceived benefits (assessment of effectiveness in avoiding the health problem if the health behavior is adopted), and (v) cues to action (events that bring on adoption of a specific behavior). If an individual believes the disease to be a threat, they may modify their health behavior in a number of ways that affect their susceptibility, the probability of encountering an infectious individual, and duration of infection. In contrast to opinions, which support adoption of health-protective behaviors, individuals may also be indifferent to health-related risks. Indifferent individuals may make little to no effort to protect their health or limit the disease spread. For example, during the AH1N1/09 ("swine flu") outbreak in 2009, people who were uncertain about the disease and felt that the extent and danger of the outbreak were exaggerated were less likely to change their behavior (21).

Individuals may form and change their opinions when being exposed to communications by a.o. health officials, newscasts, social media, and interpersonal interactions. Ideally, communications by health officials provide accurate information about an epidemic outbreak and possible self-protective measures that individuals can adopt. On the other hand, social media and interpersonal communications can be carriers of misinformation and opinions that may downplay or exaggerate the risks of acquiring infection. Individuals may feel a pressure to conform to their social environment and may adopt an opinion even if it contradicts available evidence or information distributed by health authorities (13). Moreover, by means of digital social media, interpersonal communications can spread more widely and rapidly than through the physical contact network, such that the propagation may be stimulated by ongoing communication in media (22).

Here, we focus on a health opinion switching process that arises due to interpersonal communication. To investigate the effect of interpersonal communication on the competition of health opinions in the population, we developed a deterministic compartmental model that stratifies the population by opinions. To improve the analytic tractability of the mathematical model, we restrict ourselves to the case of two mutually exclusive opinions, namely health-positive and health-neutral. While health opinions in reality can range on a continuous scale between health awareness and indifference (23), our choice can also be justified by the argument that health-related behavior is either practiced or not. So, we assume that holding the health-positive opinion invariably leads to adoption of health-protective measures in the face of an outbreak (e.g., mask wearing, increased hands washing, and keeping a distance of 1.5 m from others), while individuals holding the health-neutral opinion will not take these measures. We note that there are studies that considered continuous health opinions, for example (17) where authors used an individual-based model, which captured probability of individuals vaccinating proportional to their vaccinating opinion.

In some of earlier modeling work, sustained circulation of two mutually exclusive health opinions required the presence of an outbreak (2, 4, 24, 25). However, frequently, the opinions persist without the disease being present. In this case, the opinion switching rates depend on the number/proportion of the carriers of these opinions. A number of studies considered models, which allowed sustained circulation of opposing opinions without the disease present (26–28). The functional definition of the opinion switching rate is an important consideration in modeling opinion dynamics. Often it is captured by a mass-action term (2, 4, 14, 19, 26, 27) that may not necessarily reflect the reality. We address both of these considerations. In our model, individuals switch between opinions as a result of communication with individuals of the opposing opinion, with a switch rate that is a positive nondecreasing function of the proportion of individuals holding the opposing opinion. Here, we consider a broad family of functions to describe the rate of switching, which includes linear, saturating, and sigmoidal functions. The model we consider is conceptually close to what is known as the generalized voter model on networks (29). In these models, each individual has one of two mutually exclusive opinions, which they can dynamically switch depending on the opinion of neighbors in the network. We couple opinion dynamics with an epidemic model by allowing the rate of switching to the health-positive opinion to depend on the disease prevalence. With respiratory diseases such as influenza or COVID-19 in mind, we consider a population that mixes assortatively by opinions. In the models without opinion dynamics, assortativity was shown to lead to epidemic growth (30). However, if assortativity also affects opinion dynamics, its effect on infection transmission is less clear. While models exist that consider effect of (1) possibility of coexistence of opinions without the disease present (26–28), (2) dynamic coupling between infection transmission and opinion dynamics (2, 4, 24, 25), and (3) assortative mixing by opinion (27) on epidemic dynamics separately, here we investigate the effect of their combination on epidemic dynamics. Understanding the combined effect of these three dynamical features can assist in developing information intervention in the public health domain.

Using bifurcation and stability analysis, we investigate the opinion distribution landscape in the absence of disease. The dynamics in a disease-free state both highlight the key considerations for the design of information intervention prior to the outbreak, as well as set the stage for epidemic dynamics in case an infectious disease enters the population. We analyze for which distributions of opinions in the population an outbreak of an infectious disease can occur, i.e., how the distribution of opinions impacts the basic reproduction number of the infection. We then explore the coupled opinion–epidemic dynamics using numerical bifurcation analysis. Finally, we describe parameter regions, for which damped/sustained oscillatory dynamics may appear, and give conditions under which a disease can be eradicated even when the basic reproduction number is above 1.

Results

A model for competing opinions

In the context of an infectious disease, we consider a scenario where two relevant mutually exclusive health opinions, $+$ and $-$, circulate in a population. We denote with $+$ a health-positive opinion, whereupon an individual holding it adapts measures that reduce the probability of contracting the disease, and $-$ denotes a health-neutral opinion such that its holder does not modify their behavior and, therefore, has higher susceptibility to infection then a holder of the health-positive opinion. We assume that the protective behavior adapted by individuals holding health-positive opinion does not diminish their transmission potential as compared to individuals holding health-neutral opinion. Thus, the population is split into individuals who hold opinion $+$, N_+ and those who hold opinion $-$, N_-. The proportion of population that holds opinion $+$ is denoted by n_+, while the proportion of population who holds opinion $-$ is n_-.

We assume that individuals regardless of their opinion have on average c social contacts per week. We use the term "social contacts" to denote interactions that may lead to switching of opinions. Additionally, we consider the possibility of assortative preference to mix with individuals of the same opinion. The degree of assortative mixing is denoted by ω, $0 \le \omega \le 1$, with ω equal to 0 describing the situation where individuals interact without regard about the opinion held (fully proportionate mixing) and ω equal to 1 denotes fully assortative mixing where individuals only mix with individuals which share their opinion. For $0 \le \omega \le 1$, ω indicates the proportion of contacts that occur only with individuals sharing the same opinion, while $1 - \omega$ fraction of contacts occur with holders of each opinion, proportionate to the proportion of respective population. For simplicity, we assume that physical contacts relevant to infection and social contact (whereupon individuals exchange information) are completely independent, i.e., change in one does not cause change in the other. This is a limiting case of a more general situation whereupon change in physical contacts affects social contacts to a certain degree. On the other hand, we assume that assortative mixing affects both types of contacts in the same degree, therefore, we apply the same constant, ω, to model assortativity in both processes.

Individuals $N_{\bar{l}}$, $\bar{l} \in \{+, -\}$ may change their opinion upon contact with individuals with the opposing opinion, N_l, $l \in \{+, -\}$, $l \neq \bar{l}$. The rate of switching is described by a proportion-dependent function $f_l(n_l)$, multiplied by social contact rate c, and the likelihood of mixing with individuals regardless of their opinion, $1 - \omega$. We assume the switch rate functions $f_l(n_l)$ to be positive, continuous and increasing, and define

$$f_l(n_l) = \frac{p_l n_l^k}{1 + \theta_l n_l^k},\ l \in \{+, -\}, \tag{1}$$

where p_l, $0 \le p_l \le 1$ is the per contact probability of switching from opinion $\bar{l}$ to opinion l, $l \in \{+, -\}$. Parameters $\theta_{\bar{l}}$, $\theta_l \ge 0$, and k, $k \ge 1$ specify the shape of the response function. Observe that the switch rate to an opinion is zero, if there are no individuals with that opinion in the population.

Depending on parameters k and θ, three types of response functions can be distinguished (Fig. 1A): (1) for $k = 1$ and $\theta_+ = \theta_- = 0$ the switch rate function is linear; (2) for $k = 1$ and $\theta_+, \theta_- > 0$ the switch rate function is saturating for large densities; and (3) for $k > 1$ and $\theta_+, \theta_- > 0$ the switch rate function is sigmoidal. In ecology, very similar functions have been derived from first principles to describe the functional response of predator population density to the density of available prey, and are known as Holling type I, II, and III functional response (31).

In this work, we investigate long-term opinion dynamics for each one of these response functions. However, note that, to describe the diffusion of innovations or opinions in a population, sigmoidal functions have been used (32). These functions capture the trend whereupon the spread of an opinion l, $l \in \{+, -\}$ is very slow as long as only a small proportion of the population holds this opinion, and slows down again when the proportion of the population N_l is large, with fast growth in between. The saturation for high proportion of individuals holding opinion l, $l \in \{+, -\}$ mimics the saturation of information effect, whereupon the information loses its impact once it has been received several times. In our model, both opinions spread according to a sigmoidal response function, possibly with different shapes. This leads to a system in which opinions compete and may either coexist or drive each other to extinction.

We assume that opinion dynamics are fast compared to the natural demographic processes, and therefore, do not include demographic processes in the model.

A model coupling opinion dynamics and epidemic dynamics

We consider a disease that follows a Susceptible–Infected–Recovered (SIR) or a Susceptible–Infected–Susceptible (SIS) model. To investigate the effect of feedback between disease dynamics and opinion dynamics on the course of an epidemic, we couple the above described framework of opinion competition with a SIR or SIS infection transmission model (Fig. 1B). For both types of disease dynamics, individuals become infected and infectious at rate λ, which depends on the prevalence of infection, i. Infectious individuals recover with rate γ, either becoming susceptible again (SIS model) or becoming immune (SIR model).

Each individual has an opinion and an infection status. We denote the proportion of total population who is susceptible and hold opinion $+$ with s_+, the proportion of total population who is infectious and hold the same opinion with i_+, and the proportion of the total population who is recovered with r_+. Similarly, s_-, i_-, and r_- denote the proportions of the total population with opinion $-$ in the respective epidemiological states.

Individuals N_+ have a lower probability of acquiring infection than individuals N_-, i.e., $\beta_+ \le \beta_-$. We assume that the measures

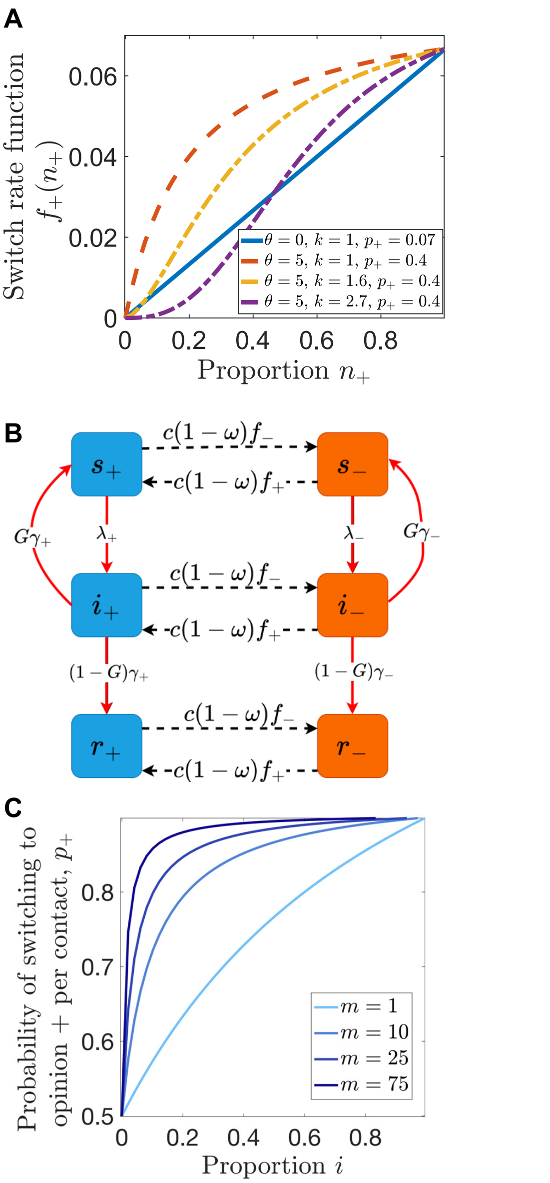

Fig. 1. Coupling of opinion dynamics and infection transmission dynamics. (A) Switch rate function to opinion + depending on proportion n_+. For $\theta = 0$ and $k = 1$ the switch rate is linear (blue); for $\theta > 0$ and $k = 1$ the switch rate is saturating (red); and for $\theta > 0$ and $k > 1$ the switch rate is sigmoid (yellow and violet). (B) Flowchart of coupled opinion and infection transmission model for two types of infectious diseases: SIS model ($G = 1$) and SIR model ($G = 0$); black dashed arrows denote opinion transitions, red solid arrows denote epidemiological transitions. (C) Per contact probability of switching to opinion + for different values of m as a function of the proportion of infected individuals, i.

taken by N_+ reduce their susceptibility only, and that infectivity and the recovery rate are the same for the two types of individuals. Note that the parameters β_+, β_- implicitly include the transmission-relevant contact rate, which may differ from the social contact rate c. We consider the case where assortativity also applies to infection-relevant contacts, such that in terms of physical contacts, the individuals can prefer to mix with individuals who have the same health opinion. Finally, we assume frequency-dependent infection transmission. Therefore, the rates with which individuals s_+ and s_- acquire infection are specified by the following equations:

Table 1. Summary of model parameters described by system (6) and ranges of values used in numerical examples.

Name	Description (unit)	Value*
c	Social contact rate (individuals/week)	10 [5,105]
ω	Degree of assortativity	0 [0,0.95]
$p_+, p_+(0)$	Probability of switching to opinion + per contact when no infectious cases exist	0.4 [0.1,1.0]
$p_+(1)$	Probability of switching to opinion + per contact when the whole population is infectious	1 [0.6,1.0]
p_-	Probability of switching to opinion − per contact	0.4 [0.1,0.4]
θ_+	Saturation constant in switch rate function f_+	5.0
θ_-	Saturation constant in switch rate function f_-	5.0
k	Switch rate function shape parameter	2.7 [0.0,2.7]
m	Constant that controls the growth rate of the switch probability p_+ as the proportion of infected individuals increases	25, 50, 75†
β_+	Infection rate of susceptible individuals holding opinion + (1/week)	0.8
β_-	Infection rate of susceptible individuals holding opinion − (1/week)	2.0 (1.5)§
γ	Recovery rate of infectious individuals (1/week)	1.0

*Outside the square brackets: default values, intervals within the brackets sampled in bifurcation and sensitivity analyses.
† Used in sensitivity analysis with respect to this parameter.
§ $\beta_- = 2$ is the default value, except for analysis presented on Fig. 7, where we used $\beta_- = 1.5$ to obtain parameter space where the dynamics of interest appear.

$$\lambda_+(t) = \beta_+\left(\omega\frac{i_+(t)}{n_+(t)} + (1-\omega)(i_+(t) + i_-(t))\right),$$
$$\lambda_-(t) = \beta_-\left(\omega\frac{i_-(t)}{n_-(t)} + (1-\omega)(i_+(t) + i_-(t))\right). \quad (2)$$

The infection status of individuals does not modify the rate with which they switch their opinion. However, infection spread in the population can affect opinion dynamics. Here, we consider the case of individuals obtaining information about disease spread that is available publicly via media and health authorities. In our model, with increasing prevalence of infection $i = i_+ + i_-$, opinion + gains in popularity, which is represented by an increase in the probability of switch to opinion + per contact, p_+. We assume that

$$p_+(i) = p_+(0) + (p_+(1) - p_+(0))\frac{(1+m)i}{1+mi}, \quad (3)$$

where $p_+(0)$ is the switching rate per contact in the disease-free state, and $p_+(1)$ is the switching rate when the entire population is infected; m is a constant that determines how fast p_+ increases with increasing prevalence (see Fig. 1C). Thus, as prevalence of infection increases, so does the switch rate to opinion + (Eq. 1). Probability of switching to opinion − per contact, p_-, remains fixed throughout the outbreak.

The dynamics are described by a flow diagram shown in Fig. 1(B) and are captured by system of ordinary differential Eq. (6) in the "Methods" section.

Model parameters are summarized in Table 1. In numerical analysis, we use the indicated parameter values, unless stated otherwise. We give the justification for the selection of the values later in the text. Most times when parameter values deviate from the ones stated in the table, the results of this variation are presented and compared on the same figure.

To calculate the basic reproduction number R_0 for this model, we used the Next-Generation Matrix method described in (33). Then R_0 is given by the spectral radius of matrix FV^{-1} with

$$F = \begin{pmatrix} n_+(0)\beta_+\left(\frac{\omega}{n_+(0)} + (1-\omega)\right) & n_+(0)\beta_+(1-\omega) \\ n_-(0)\beta_-(1-\omega) & n_-(0)\beta_-\left(\frac{\omega}{n_-(0)} + (1-\omega)\right) \end{pmatrix},$$

$$V = \begin{pmatrix} \gamma_+ + c(1-\omega)f_-(n_-(0)) & -c(1-\omega)f_+(n_+(0)) \\ -c(1-\omega)f_-(n_-(0)) & \gamma_- + c(1-\omega)f_+(n_+(0)) \end{pmatrix}. \quad (4)$$

Here, $(n_+(0), n_-(0))$ are given by the opinion distribution at the start of the outbreak and depend on $k, \theta_+, \theta_-, p_+/p_-$.

For a population, in which only one of the two opinions is present ("mono-opinion" population), the epidemic dynamics are reduced to the basic SIS/SIR dynamics with a basic reproduction number that is determined by the parameters of the dominating opinion:

$$R_0^l = \frac{\beta_l}{\gamma_l}, \; l \in \{+, -\}. \quad (5)$$

Dynamics of competing opinions

To understand the effect of the coupling between the disease spread and opinion competition on infection transmission, we first need to consider the dynamics of opinions in the disease-free population.

The model indicates that when either one of the two opinions dominates the population ("mono-opinion" population), then this remains unchanged until individuals of the opposing opinion enter the population from outside. As we are mainly interested in situations where two opinions compete in the population, we investigated for which parameter regions a stable coexistence of two opinions is possible. This coexistence depends on the shape of the switch rate functions, f_l, $l \in \{+, -\}$, but not on the social contact rate c or the assortativity parameter ω, as these are assumed to be the same for both opinions (Supplementary information, Supporting information text).

Linear switch rate function dynamics

For this switch rate functions (Eq. (1), $\theta_l = 0, l \in \{+, -\}, k = 1$), the stable coexistence of opinions is not possible (Figure S1). Due to impossibility of stable coexistence between opinions in a disease-free population, we do not consider the dynamics of the model given the linear switch rate. Full treatment of opinion dynamics for this shape of opinion switch can be found in the Supplementary information, section *Dynamics of opinion competition with a linear switch function*, Figure S1.

If the switch rate functions are nonlinear (Eq. (1), $\theta_l > 0, l \in \{+, -\}, k \geq 1$) the opinions can coexist in a steady state (Fig. 2).

Saturating nonsigmoidal switch rate function dynamics

For these switch rate functions ($\theta_l > 0, l \in \{+, -\}, k = 1$), either stable coexistence is possible, or one of the mono-opinion solutions is stable. It depends on the two switch rate functions, whether coexistence is possible or not (Fig. 2A, D, and G). Stable coexistence of opinions is possible in the case when the switching functions exhibit saturation at high proportion of an opinion. Subsequently, the growth of the switch rate function for the dominant opinion slows down when the majority of the population is following that opinion. The stable coexistence state is attracting for all initial situations, in which both opinions are present. The distribution of opinions at this steady state depends entirely on the ratio p_+/p_- and not on p_+ and p_- separately (Supplementary information, Supporting information text). The larger the ratio p_+/p_-, the higher is the equilibrium proportion of N_+ individuals. If permanent coexistence of opinions is impossible, the opinion with higher switch rate per contact (p_l, $l \in \{+, -\}$) will take over the population. The interval of p_+/p_-, in which opinions can coexist, depends on the saturation constants of the switch rate functions, θ_l, $l \in \{+, -\}$. The higher these are (i.e., the faster saturation is achieved) the wider is the p_+/p_- interval, in which opinions can coexist. Intuitively, the faster the switch rate functions become saturated, the larger differences between the probabilities of switching per contact can be while still allowing stable coexistence of opinions. For mathematical derivations and further elaborations, see Supplementary information, Supporting information text.

Sigmoidal switch rate function dynamics

If the switch rate functions are sigmoidal (Eq. (1), $\theta_l > 0, l \in \{+, -\}$, $k > 0$), at least one stable coexistence state of opinions is possible for some parameter regions (Fig. 2B and E). Additionally, mono-opinion population states are always locally attracting; i.e., if, for example, the population starts with a sufficiently large majority believing opinion +, then after some time the entire population will hold this opinion.

If there is only a single unstable coexistence equilibrium (Fig. 2B and C), the population always ends up as a mono-opinion population, but it depends on the initial distribution of opinions to which opinion it will converge. The proportions of n_+ and n_- at this unstable steady state depend on the ratio p_+/p_-. The higher this ratio, the lower is n_+. This unstable equilibrium separates the state space into the basins of attraction of the +-mono-opinion and −-mono-opinion populations. This implies that the population with the higher associated switch probability per contact p_l, $l \in \{+, -\}$ requires a smaller proportion of individuals of that opinion to invade. This is illustrated in Fig. 2(G), where p_+ is 1.5 times higher than p_-, hence it requires much fewer individuals of opinion + to take over the population.

If, on the other hand, several steady states are possible, then their number is odd and at least one of them is locally attractive. For the interpretation of the model, only locally stable steady states are of interest as states in which two opinions can coexist. Unstable steady states are relevant as boundaries between basins of attraction. In our numerical experiments, we observed at most three different steady states, one of them a stable coexistence state (see Fig. 2B). Our analysis and numerical experiments indicate that existence of a stable coexistence state of opinions depends on values of p_+/p_-, θ_+, θ_-, and k (Supplementary information, Supporting information text).

If there are three steady states, two of them are repelling and one is attracting, such that the proportion n_+ for the attracting state is between the proportions n_+ for the repelling states. Therefore, the repelling states mark the boundaries of the basins of attraction for the attracting states. From the bifurcation diagram (Fig. 2B), we observe that there are two points where the dynamics of the system change as p_+/p_- increases from zero (left and right edges of the green region on Fig. 2B). These are saddle node bifurcation points, which mark the appearance and disappearance of a pair of steady states. If p_+/p_- is to the left of the green region, then in order to take over the population, nearly the whole population should hold opinion +. Stable coexistence of opinions is

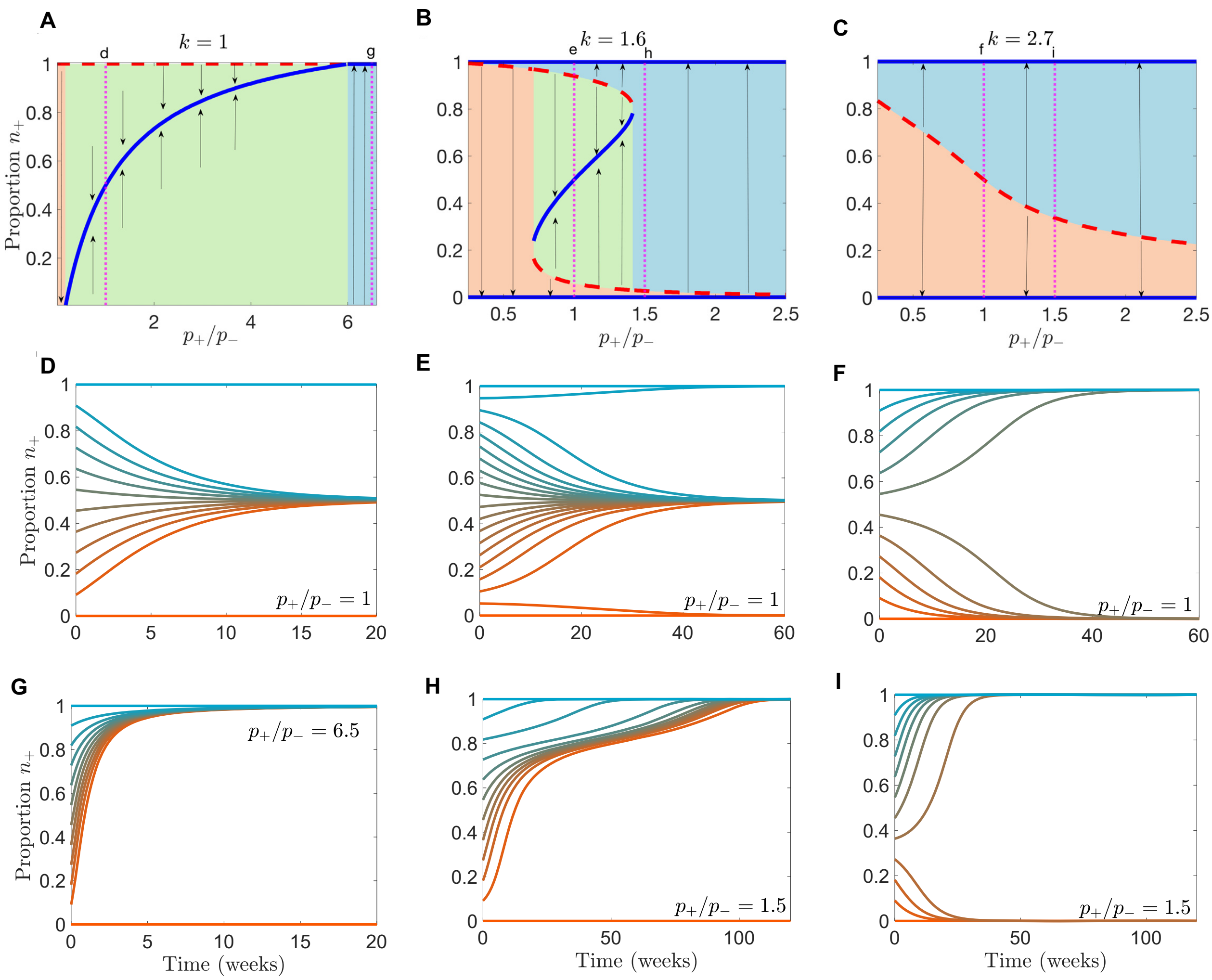

Fig. 2. Opinion competition dynamics for saturating and sigmoidal switch rate functions. The upper row shows bifurcation diagrams of n_+ as a function of p_+/p_-. For (A) a saturating switch rate function; (B) and (C) sigmoidal switch rate functions. Dashed red lines: unstable equilibria, solid blue lines: stable equilibria. Orange area: basin of attraction for the equilibrium with opinion—dominating; blue area: basin of attraction for the equilibrium where opinion + dominates; green area: basin of attraction of a stable coexistence equilibrium. Dotted magenta lines denote parameter settings used to generate the time series on panels (D)–(I), in respective columns. (D)–(I) Temporal dynamics of n_+ for different switch rate functions and ratios p_+/p_-. In all panels $\theta_+ = \theta_- = 5$.

impossible. As p_+/p_- increases and passes the left edge of the green region, this proportion n_+ needed for opinion + to take over the population declines (Fig. 2B, upper red curve in the green region). More importantly, stable coexistence with opinion—is now possible and requires a much smaller initial proportion of n_+ for persistence of +. (Fig. 2B, lower red curve in the green region). As p_+/p_- increases past the right edge of the green region, the "invasion" proportion threshold for opinion + further declines. Moreover, as stable coexistence is not possible anymore, it becomes the threshold for complete taking over of the population by opinion +.

Epidemic dynamics in a population with competing opinions

For the purposes of analysis of the feedback between opinion competition and infection dynamics, we are mainly interested in the situation where health-positive and health-neutral opinions can coexist in a steady state and the mono-opinion population steady states are locally stable. We, therefore, focus our attention on sigmoidal opinion switch rate functions and on the parameter region where stable coexistence of opinions is possible. We assume that an infectious disease invades a population, in which the two opinions coexist at the stable steady state.

The opinion switch rate-related parameters are fixed at $k = 1.6$, $\theta_+ = \theta_- = 5$. Thus, the switch rates for both opinions are sigmoidal functions. We fix $p_- = 0.4$. For most of the simulations p_+ and $p_+(0)$ are fixed to 0.4, thus $p_+/p_- = 1$ and the stable coexistence of opinion equilibrium has 50/50 distribution of health-positive and health-neutral individuals. Probability of switching to opinion + per contact when the whole population is infectious $p_+(1)$ is bounded by the largest possible value it can have, 1. Assortativity degree ω is varied on the largest biologically meaningful interval [0,0.95] to recover full range of qualitative dynamics.

Social contact rate c was selected for some of the simulations to be equal to 10 individuals per week. We assumed this baseline value since the social contact rate describes interactions that can lead to opinion switching and we assume that such exchanges are much rarer than standardly reported number of close-proximity contacts per week (98 contacts for the Netherlands per POLYMOD study (34)). We explored sensitivity of the outcomes to this parameter by considering a larger ranges of 5 to 100 individuals per week.

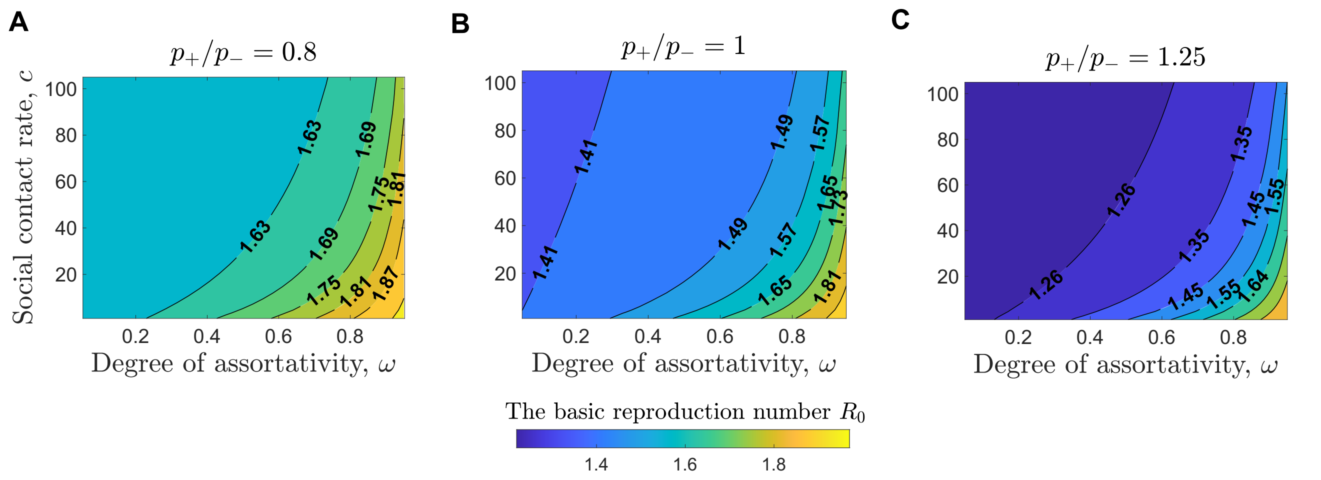

Fig. 3. Impact of mixing patterns on basic reproduction number R_0. (A), (B), and (C) show contour maps of R_0 as a function of the social contact rate c and the assortativity ω. (A) For $p_+/p_- = 0.8$ the initial distribution of opinions is $(s_+(0), s_-(0)) = (0.35, 0.65)$. (B) For $p_+/p_- = 1$ we have $(s_+(0), s_-(0)) = (0.5, 0.5)$. (C) For $p_+/p_- = 1.25$ we have $(s_+(0), s_-(0)) = (0.65, 0.35)$. The infection rate of susceptible individuals holding opinion—is fixed $\beta_- = 2$, the value used to investigate the dynamics for the SIR system. For the same set of figures with $\beta_- = 1.5$, the value used to investigate the dynamics of the SIS model, see Figure S2.

We consider the dynamics of a respiratory nonfatal infectious disease whose transmission dynamics and stages of infection course are similar to flu. We assume that the infectious period lasts on average a week, thus we fixed $\gamma_+ = \gamma_- = 1$ per week. Furthermore, we assume that in a population where opinion + is dominant, the infection cannot spread because the health-positive opinion leads to protective behavior that prevents an outbreak of the infection. In a population, where opinion—dominates, this health-neutral opinion enables the infection to spread. The transmission parameters are set as follows. The infection rate of susceptible individuals holding the health-positive opinion + is fixed $\beta_+ = 0.8$ per week, and the infection rate for individuals holding the health-positive opinion—is fixed $\beta_- = 2$ per week for SIR model and $\beta_- = 1.5$ per week for SIS model. This difference of values was necessary, since in the case of SIS the pool of susceptible individuals is being constantly replenished. These settings imply that $R_0^+ = 0.8 < 1$ and $R_0^- = 2 > 1$.

Basic reproduction number

In a situation where both opinions are present at the time the infectious disease comes into the population, the basic reproduction number R_0 depends on the proportions n_+ and n_-. We assume that these proportions are at steady state at the moment of onset of an epidemic. Recall that c and ω do not influence this steady state distribution of opinions, so the initial situation is the same for all values of those parameters. We, therefore, can investigate how social contact rate c and degree of assortativity ω impact the epidemic dynamics without changing the initial steady state of the system. By varying c and ω, we change the way the population can adapt to an emerging outbreak by communicating about health-positive behavior. With increasing c, opinions can spread faster, while with increasing ω, opinions are more restricted to their subpopulation.

In Fig. 3, we investigated how the basic reproduction number R_0 changes with changing social contact rate c and assortativity degree ω for three settings of the ratio p_+/p_-: 0.8, 1, and 1.25.

For all three settings of ratio p_+/p_-, the basic reproduction number increases as assortativity ω increases, and decreases as the social contact rate (c) increases. As the ratio p_+/p_- increases, the basic reproduction number decreases. We note that for high assortativity, the effect of increasing c is smaller than for low assortativity. Overall, we conclude that increasing assortativity slows down the spread of opinions and therefore leads to higher values of R_0. Conversely, increasing social contact rate c leads to faster opinion spread and, therefore, to lower R_0. Therefore, strong assortative mixing by opinions can facilitate the outbreak of an infectious disease. For sensitivity analysis of the basic reproduction number to changes in the infection rates of N_+ and N_- individuals by type of infection (SIR and SIS) see Figure S3.

SIR model with opinion competition

In this section, we consider the dynamics beyond the start of an outbreak for an SIR-type disease and investigate how it depends on c and ω. We fixed $p_+(0)/p_- = 1$ and $p_+(1)/p_b = 2.5$ and used the respective stable coexistence distribution ($n_+ = 0.5$, $n_- = 0.5$) as the initial state of the population. We seeded infection by setting $i_-(0) = 6 \times 10^{-8}$ and $s_-(0) = n_-(0) - i_-(0)$.

We start by investigating the effect of the feedback between opinion competition and infection dynamics on the epidemic peak and on the peak proportion of the population holding opinion +, n_+ during and after the outbreak. We used three settings for parameter m, which affects the sensitivity of the population to the growth in prevalence of infection. As the prevalence increases, p_+ now increases, and this can be slower ($m = 25$) or faster ($m = 75$) (Fig. 4).

For all three scenarios, the peak prevalence is higher for lower contact rates and higher assortativity. The higher is the sensitivity of the population m, the lower is the prevalence peak.

From Fig. 4, it follows that as a consequence of the feedback between the disease and infection dynamics, the proportion of individuals who hold opinion + temporarily increases, with eventual return of the population to the preoutbreak opinion distribution. However, for some parameters settings, the population may switch completely to opinion +, thereby preserving the memory of the past outbreak. We investigated the parametric region, in which this conversion to + occurs (Fig. 4 and Figure S5). From these figures, it follows that high sensitivity of the population to rise in prevalence of infection, as reflected in parameters $p_+(1)$ and m and a high social contact enable conversion to opinion +. In addition, a high degree of assortativity also enables opinion + to become dominant (dark blue region in Fig. 4(A)–(C) and in Figure S6a

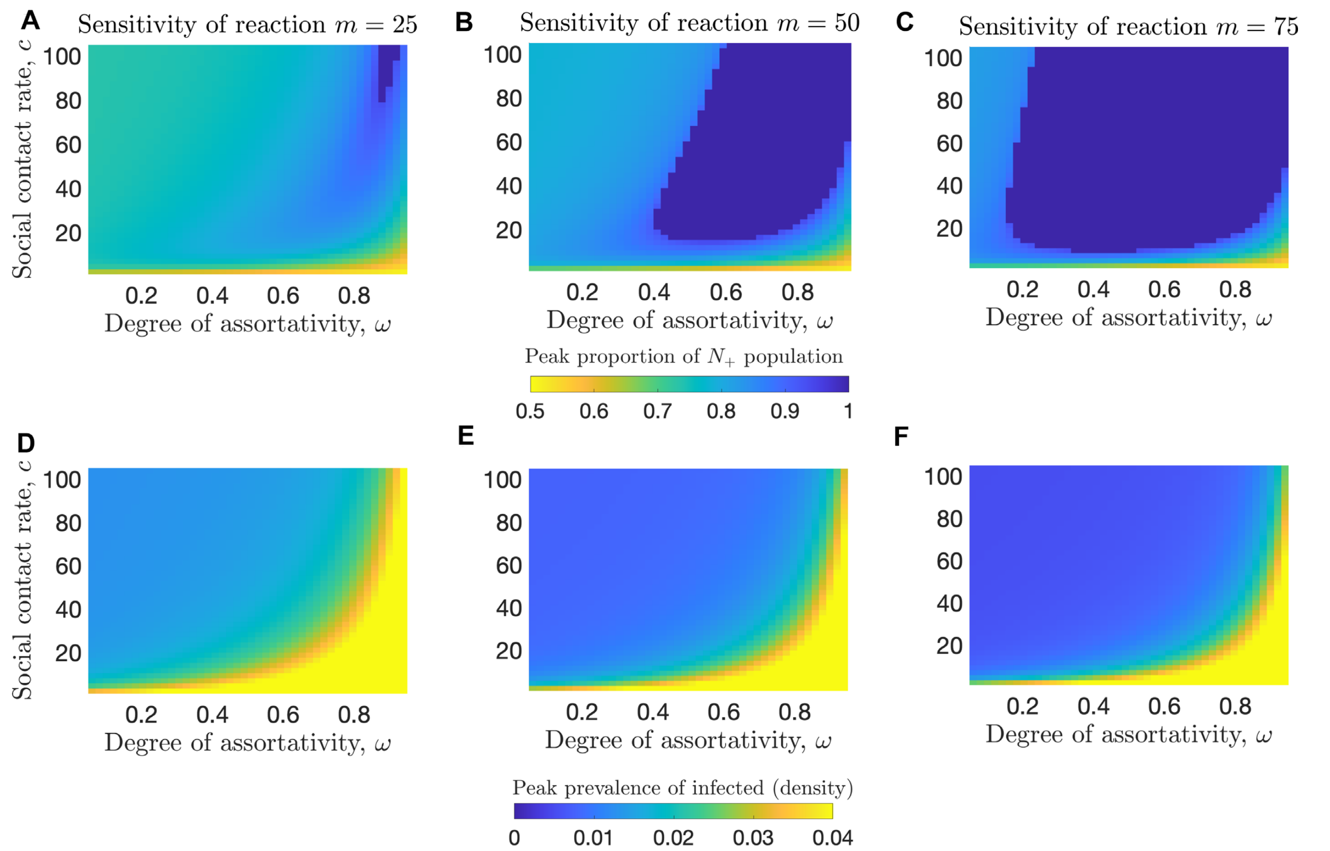

Fig. 4. Impact of social contact rate and assortativity on epidemic dynamics. We consider the dynamics of the SIR system for three scenarios for the sensitivity of the population to increasing prevalence of infection as denoted by parameter m, $m = 25$ for (A) and (D), $m = 50$ for (B) and (E), and $m = 75$ for (C) and (F). (A), (B), and (C) show heat maps of the peak proportion of the individuals with opinion +, n_+ population; in the dark blue region the population switches to opinion +. (D), (E), and (F) show contour maps of the peak prevalence.

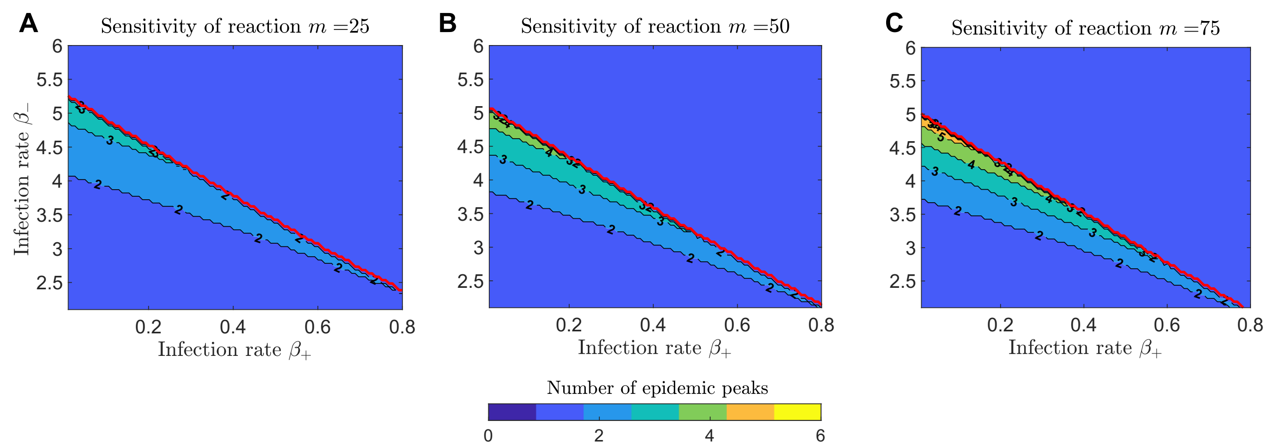

Fig. 5. Regions of multiple epidemic peaks resulting from feedback between disease dynamics and opinion dynamics. We consider the dynamics of the SIR model. (A), (B), and (C) are contour plots of the number of prevalence peaks for different values of infection rates β_+ and β_- for different sensitivity m of the population to increasing prevalence: (A) $m = 25$, (B) $m = 50$, and (C) $m = 75$. The social contact rate is fixed at $c = 40$, and the probability of switch to opinion + per contact when the entire population is infected is fixed $p_+(1) = 1$, and the assortativity degree is fixed $\omega = 0$. The area above the red curve denotes the outcome where the population switched to opinion +. As m increases this region expands.

and S6b). This is unexpected, since high assortativity slows down opinion exchange. However, since high assortativity also leads to a large R_0, it leads to a rise in prevalence, and therefore, increases the probability of switching to opinion +. For a technical explanation of the opinion switch, see section *Effect of opinion competition on population opinion switch during epidemic*, Figure S7.

We conclude this section by discussing effect of the feedback dynamics on transient dynamics of an SIR model and the role of parameter space in their appearance. In contrast with the standard SIR epidemic, whose dynamics display a single peak only, in a situation with feedback between the disease dynamics and opinions dynamics multiple epidemic peaks may appear (Fig. 5).

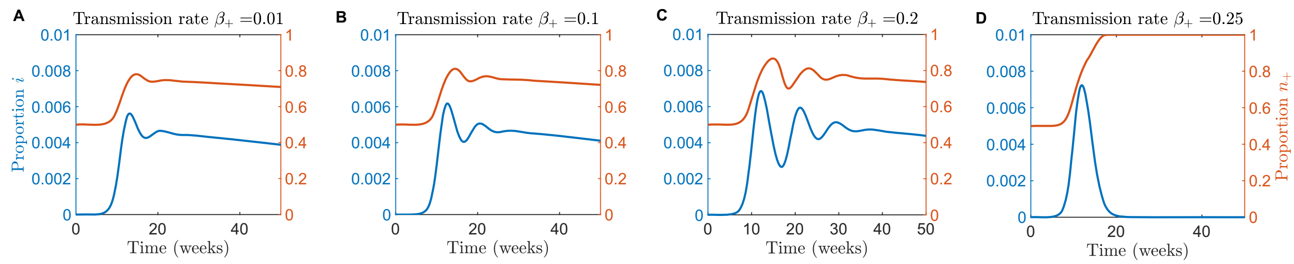

Fig. 6. Temporal dynamics with multiple epidemic peaks resulting from feedback between disease dynamics and opinion dynamics. We consider the dynamics of the SIR system. Panels show time series of infection prevalence, and of the proportion of individuals holding opinion $+$, n_+, n_+ for different values of infection rate β_+. The social contact rate was fixed at $c = 40$, the upper bound of the probability of switching to opinion + was set to $p_+(1) = 1$, the sensitivity parameter m was set to $m = 75$, the infection rate of N_- individuals was set to $\beta_- = 4.15$, and the assortativity degree is fixed $\omega = 0$.

Our numerical analyses indicate that in order for multiple epidemic peaks to appear there should be a pronounced difference between population N_+ and N_- in terms of the preventative measures they adapt (as reflected in parameters β_+ and β_-). The upper boundary of the region in $\beta_+ - \beta_-$ subspace where multiple peaks appear marks the region where the population switches to opinion + (red curve). Therefore, for a fixed β_- as β_+ increases multiple peaks appear as the population moves to the +-mono-opinion state (Fig. 6). The number of peaks grows as β_+ moves closer to the boundary. Note that in our analyses, we considered a local maximum of prevalence to be a peak if it exceeded 10^{-8}.

Moreover, the more sensitive the population is to increases in the prevalence of infection (as reflected by parameter m), the larger is the number of peaks that will appear in the region adjacent to the boundary where switch of the population to opinion + occurs, see Fig. 5 and Figure S5. Finally, if the probability of switch to opinion + in the population without infection, $p_+(0)$ is significantly smaller than the probability of switch to opinion −, p_- the region in $\beta_+ - \beta_-$ space where multiple peaks exist is larger (see Figure S4).

In summary, for SIR-dynamics we find that feedback between opinion dynamics and epidemic dynamics can substantially change the epidemic outcomes. The basic reproduction number R_0 and the peak of an outbreak can be higher if there is assortative mixing by opinion. In addition, multiple epidemic peaks can occur and the response to an epidemic can lead to a shift of the population to a state, in which only the health-positive opinion is circulating.

SIS model with opinion competition

Similarly, for a SIS-infection, coupling between opinion competition and disease dynamics can lead to opinion + taking over the population (Fig. 7), and to the appearance of oscillatory epidemic dynamics (Fig. 8). For the SIS epidemic, these oscillatory dynamics can be sustained epidemic cycles instead of damped oscillations.

We start by investigating combination of conditions that may lead to switching of the whole population to opinion + and subsequently to lead to the disease to go extinct even when $R_0 > 1$ for the opinion coexistence state. Our results indicate that higher sensitivity of the population to increasing prevalence, as reflected in high values of m and $p_+(1)$, will result in higher average densities of n_+, and for some regions $n_+ = 1$ (Fig. 7 and Figure S8). The higher is the value of m the lower is the threshold value of $p_+(1)$ above which the population switches to opinion +. Moreover, if p_+ is larger than a threshold value, the state $n_+ = 1$ occurs for a wide range of sensitivity of the population to the prevalence, m. Should $p_+(1)$ exceed the threshold value significantly, the prevalence reduces considerably. Finally, high degree of assortativity in the population, on the one hand, leads to higher endemic prevalence. On the other hand, high assortativity leads to increase in the $p_+(1) - m$ subspace where the population switches to opinion +. We hypothesize that this is attributed to the positive effect assortativity has on infection transmission.

Next, we investigate the conditions when the feedback between opinions competition and disease spread can induce sustained oscillatory epidemic dynamics (Fig. 8). We investigated the conditions under which this may happen. We discovered that oscillatory dynamics mostly require a pronounced difference in epidemiological properties between individuals N_+ and N_-, such that when the whole population holds opinion +, the disease becomes extinct and if the whole population holds opinion—the disease persists. To show this, we plotted the amplitude of the epidemic cycle, its period and average value across an interval of infection rates values for two different sensitivities of the population reaction to the prevalence of infectious cases.

For a fixed value of infection rate of N_- individuals, $\beta_- = 5.5$, as infection rate of N_+ individuals β_+ increases initially, the endemic prevalence of infectious cases is constant in time, with the prevalence level increasing (Fig. 9A). Once β_+ increases past a threshold value, the constant endemic state is replaced by oscillatory dynamics, such that the average prevalence decreases as compared to the constant level it replaces (Fig. 9B). As β_+ increase further, the average prevalence, magnitude, and period of the cycle increase (Fig. 9C). This pattern continues until the prevalence pushes the population to switch to opinion +, at which point the prevalence becomes zero and oscillatory dynamics disappear (Fig. 9D).

To summarize, given a disease that follows SIS framework, adaptive behavior can lead to a number of qualitatively different outcomes. It can lead to the reduction of infection prevalence, appearance of sustained epidemic cycles, and complete eradication of the infection in conditions where the basic reproduction number would indicate that the infection will persist. Moreover, as the degree of assortativity increases, and therefore, the basic reproductive number increases, the parametric region where opinion + becomes dominant becomes wider. Similar to the SIR model, the parameter region where oscillations arise is adjacent to the region where opinion + becomes the dominant opinion.

Discussion

Using a model that couples opinion competition and infection spread, we investigated the effects of feedback between the two on epidemic dynamics. Our main findings were that the opinion distribution landscape can significantly influence the outcome of an epidemic. On the one hand, epidemic peaks can be reduced, and a population can be completely shifted into a health-positive

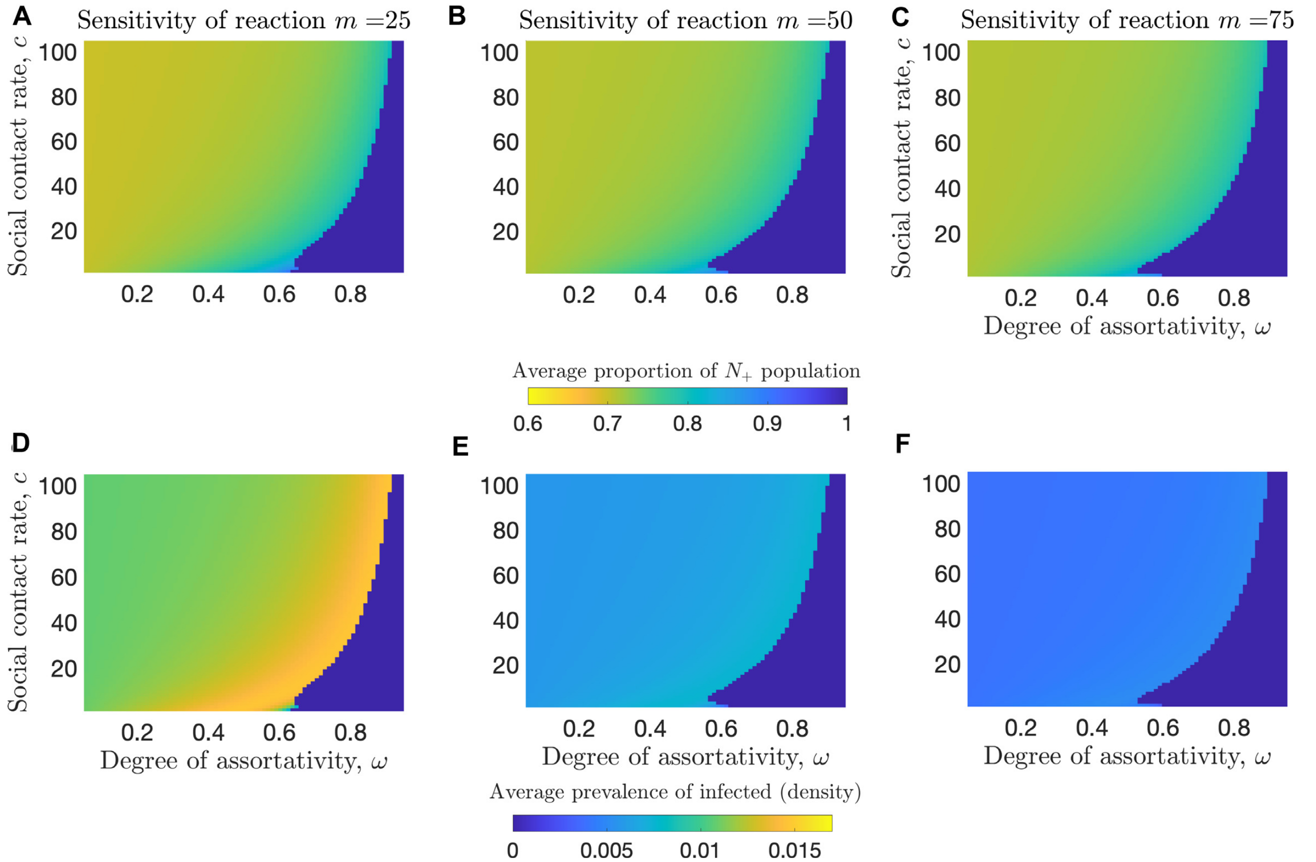

Fig. 7. Impact of social contact rate and assortativity on the average endemic prevalence of infectious cases and average long-term opinion distribution. We consider the dynamics of the SIS system. (A), (B), and (C) show heat maps of the long-term average proportion of the population holding opinion +. (D), (E), and (F) show heat maps of the long-term average infection prevalence. If the epidemic dynamics are periodic, then the average is taken over the period. (A) and (D) show scenarios with sensitivity of reaction to prevalence given by $m = 25$. (B) and (E) show scenarios with sensitivity of reaction to prevalence given by $m = 50$. (C) and (F) show scenarios with sensitivity of reaction to prevalence given by $m = 75$. The dark blue region in the top row and dark blue region in the bottom row denote the outcome where the population switched to opinion + and the disease becomes extinct. The infection rate of N_- individuals was set $\beta_- = 1.5$.

state. The appearance of this epidemic transition as the result of the opinion and infection feedback is reminiscent of the dynamics observed by Velásquez-Rojas and Vazquez (35) in a epidemiological model, which coupled SIS disease with a voter opinion dynamics model. On the other hand, damped or sustained oscillations of prevalence can appear as transmissibility of the infection increases. Parameters related to socializing dynamics such as social contact rate and degree of the assortative mixing by opinion were among the most important factors leading to the appearance of the above phenomena.

Social contact rate was shown to have inverse relationships with epidemic peak size. For SIR-type of the disease, increase in social contact rate promoted decrease in the peak size of the epidemic. For SIS-type of the disease, if the feedback dynamics between opinion and transmission did not drive the population to adapt the health-positive opinion, increase in the social contact rate caused decrease in prevalence. However, for a high enough contact rate, the possibility of the health-positive opinion taking over disappeared. This unexpected result is in line with findings of Silva et al. (25) and Velásquez-Rojas et al. (36). More specifically, Velásquez-Rojas et al. (36) showed that increasing the speed of information process has the effect of increasing the prevalence for an SIS-type of the disease.

The influence of assortative mixing is 2-fold. On the one hand, assortative mixing slows down the switching of opinions and, therefore, the possible reaction of the population to an epidemic. On the other hand, as the basic reproduction number increases as the assortative mixing increases, higher assortative mixing leads to higher incidence and, therefore, to a stronger reaction of the population, eventually even pushing the population into a state where the health-positive opinion is dominating. However, if assortativity is too high, its promoting effect on prevalence is not sufficient to help spread the health-protective opinion, and the population will experience a large epidemic peak. This effect on opinion spread is mitigated if the social contact rate is high.

Our model differs from some of the earlier work incorporating awareness into epidemic modeling (2, 4) in that we consider both opinions as possibly equally attractive under certain conditions, such that a health-positive individuals may switch to a health-neutral opinion through contact with others who hold that opinion. This switching, which leads individuals to adopt a more risky health behavior, can therefore, spread in the same way as health-positive behavior. This approach was previously considered to model concurrent spread of the fear of a disease and spread of the vaccination in the presence of infection (37). In the papers (2, 4), awareness for the risks of infection decayed, when the infection was not present in the population, eventually leading to a completely unaware population. In contrast, in our model both opinions can coexist in a steady state, also in a disease-free situation. The possibility of this outcome depends on the shape of opinion

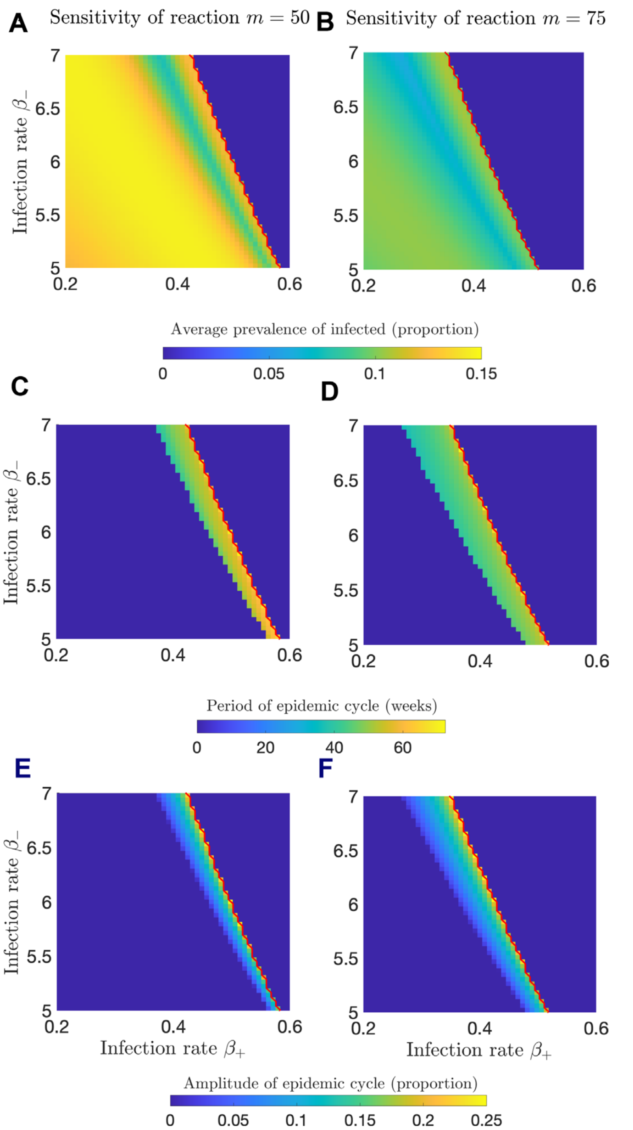

Fig. 8. Impact of assortativity and sensitivity of reaction to the prevalence of infectious cases on the appearance of periodic epidemic dynamics. We consider the dynamics of the SIS system. (A) and (B) show heat maps of the average prevalence. If the epidemic dynamics are periodic, then the average is taken over the period. (C) and (D) show heat maps of the period of the epidemic cycle. The period is equal to zero if the dynamics are stationary. (E) and (F) show heat maps of the amplitude of epidemic cycle. The amplitude is zero if the dynamics are stationary. (A), (C), and (E) show scenarios with sensitivity of reaction to prevalence given by $m = 50$. (B), (D), and (F) show scenarios with sensitivity of reaction to prevalence given by $m = 75$. The dark blue region above the red line denotes the outcome where the population switched to opinion + when no infectious cases are present and the disease becomes extinct. The probability of switch to opinion + when no infectious cases are present is fixed $p_+(0) = 0.28$, the probability of switch to opinion + when the whole population is infected is fixed to $p_+(1) = 0.6$. Social contact rate is fixed $c = 10$.

switch rate function. The potential of a stable coexistence of the two opinions implies that the impact of a new epidemic depends on the initial proportion of individuals with a health-positive opinion. Such an initial situation can be influenced, e.g., by educational interventions or other types of communication about future epidemic risks.

Appearance of oscillatory epidemic dynamics due to the feedback between health opinion dynamics and disease spread was observed both in the analysis of real world data (1, 5) and simulated trajectories produced by socio-epidemiological models (38–44). In the present work, by means of considering changes in the dynamics across the parameter landscape, we gained insights into which properties of the system cause the appearance of oscillations. Pronounced difference between the carriers of two opinions in terms of infection rates as well as high average infection rate is one of the conditions for which oscillatory dynamics arise. Another important factor for the appearance of oscillations is a high rate of opinion exchange (as captured by the social contact rate) and high sensitivity of the population to prevalence. This latter result falls in line with findings by Glaubitz and Fu (40), who found that increased sensitivity (responsiveness) to the epidemic decreases amplitude of oscillations, but increases the duration of oscillatory dynamics. These two factors also contribute to the possibility of the population switching to the health positive opinion. In our experiments, the parametric regions where these two phenomena take place always appeared adjacent to each other. In our work, the increase in switch to health-positive opinion depends on prevalence of infectious cases, which means that prevalence is instantaneously translated to change in popularity of the opinion. However, if as is the case with COVID-19, popularity of health-positive opinion depends on another statistics (such as hospitalizations or death), then there appears to be a lag between appearance of new cases and update of public awareness of the disease. Weitz et al. (41) showed that this lag can lead to appearance of oscillatory dynamics.

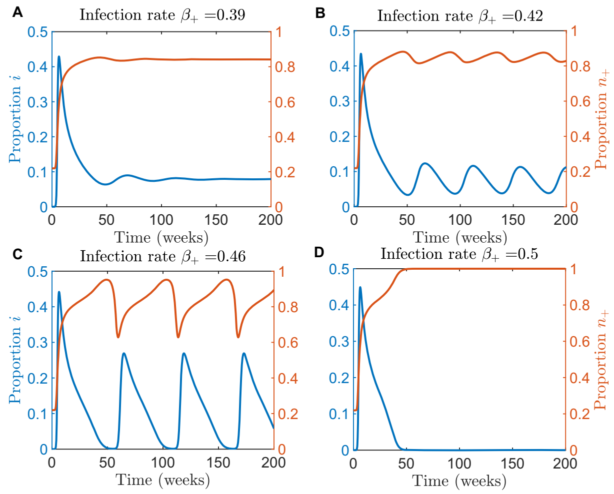

Fig. 9. Sustained oscillatory dynamics resulting from feedback between disease dynamics and opinion dynamics. We consider the dynamics of the SIS system. Panels show time series for the prevalence of infectious cases and for proportion of individuals with opinion +, n_+, for different values of infection rate of N_+ population, β_+. The contact rate for information exchange is fixed $c = 10$, the probability of switch to opinion + when no infectious cases are present is fixed $p_+(0) = 0.28$, the probability of switch to opinion + per contact when the whole population is infected is fixed $p_+(1) = 0.6$, the constant that controls the growth of the switch rate to opinion + is fixed $m = 75$, and the infection rate of N_- individuals is fixed to $\beta_- = 5.5$.

The model can be extended to address present-day epidemic concerns, such as dynamics of infectious vaccine-preventable diseases. Vaccine uptake rate for well-known infectious diseases (e.g., measles and influenza) as well as for emerging ones (e.g., COVID-19) is fraught by reluctance of the part of the population to vaccinate (45–49). While circulation of vaccine uptake-endorsing opinions is subject to both communication from public health authorities as well as to interpersonal exchanges (46, 50, 51), the circulation of antivaccination sentiment depends on social norms within the local network and interpersonal communications within the network (50–52). The models that considered the role of interpersonal communications on the vaccination uptake and its effect on epidemic dynamics (38, 39), while coupling vaccination strategies with the population epidemic state, modeled the growth of the vaccinating population contingent on the presence of the disease, while its opposite, nonvaccinating sentiment, did not depend on the population state. Our framework, which allows for symmetric treatment of health-positive and health-neutral sentiments is well-suited for investigation of vaccination opinion dynamics with or without the disease.

Out of consideration for transparency of presentation and to focus on the feedback effect, we developed our model using ordinary differential equations and thus, assumed a mass-action mechanism. However, for many infectious diseases (e.g., sexually transmitted infections), representation of population as a multiplex network will be more accurate. Our model can serve as a basis for such models. A large body of work exists using individual-based models to investigate effect of social and physical interaction networks on dynamics of competing processes, such that spread of one affects spread of another (36, 53–57).

Another use for disease-behavior coupled individual based frameworks is to investigate spatial spread of an infection, especially in the case where aware individuals modify their contact patterns as a response to perceived danger from contracting the disease (58). Similar to our findings, and findings of Perra and colleagues (4), Epstein and colleagues (58) observed that if individuals can recover from the aware state, the epidemic dynamics may include several waves.

Our framework can bring interesting qualitative insights for the dynamics of a vaccine preventable disease characterized by waning immunity (e.g., measles, pertussis, and influenza). In the conditions of waning immunity, it is highly important to keep up consistently high vaccination uptake rate if not to eradicate the disease, at least to avoid the overcrowding of the health care system. Another important consideration, in the context of infectious diseases characterized by waning immunity, is the process of waning and boosting of immunity which can cause pronounced oscillation dynamics (59). Therefore, for infectious diseases characterized by waning and boosting of immunity, presence of adaptive behavior with respect to vaccination, can give rise to rich dynamics highly relevant for the efforts of health authorities.

In this work, we made a number of simplifying assumptions. First, we assumed that the social exchange does not necessarily require physical contacts (interactions that have a probability of infection transmission), i.e., in a situation where the physical contact may decrease, the information exchange and thus, opinion dynamic will proceed unimpeded. However, in real life, at least some of the social contacts will terminate if the physical contact rate is reduced. Thus, if health-positive individuals practice social distancing then opinion dynamics and subsequently epidemic dynamics will be altered in a number of ways that may not necessarily benefit the population. For example, given a reduction of social contact rate for the health-positive individuals, it may be necessary they are present at a higher proportion, in order to maintain steady presence in the population. Second simplifying assumption that we made is that assortativity in social contacts is equal to assortativity in physical contacts, while the former can be greater than the latter. The result of the relaxation of the equal assortativity assumption is not straightforwardly apparent and represents an avenue for future investigation. Finally, we assumed that the effect of holding the health-positive opinion manifests itself as the adoption of measures designed to reduce susceptibility (e.g., washing hands and influenza). This assumption had a distinct effect on the dependence of the force of infection term on the proportion of infectious individuals. If, for example, individuals holding the health-positive opinion have also adopted measures that reduce their infectivity (e.g., mask wearing, stayig at home while sick), then the infection force term would have to account for the reduction in potential to infect as well. Note, that it was shown in (20) that when the health-positive opinion spreads fast, different prevention measures (that affect either susceptibility or infectivity or both), produce similar result if their efficacies are the same. Moreover, the effect of several such measures being adopted is additive.

Our simple model has rich dynamics, appearance of which depends on the functional responses and parameter values. For example, as our analyses have shown, the shape of the functional response plays a key role in the dynamics of health opinions/behaviors and subsequently in epidemic dynamics. Therefore, to be able to use the model for qualitative and quantitative predictions it is paramount to accurately identify functional representations for the opinion switch rates and for behavioral response to the epidemic spread. Having these at hand will enable the design of information interventions to be well-tailored to the specific time frame of the epidemic.

Materials and Methods

The system of ordinary Eq. (6) describes the coupled dynamics of infection spread and opinion competition.

$$
\begin{aligned}
\frac{ds_+(t)}{dt} &= -s_+(t)c(1-\omega)f_-(n_-(t)) + s_-(t)c(1-\omega)f_+(n_+(t)) \\
&\quad - s_+\lambda_+(t) + G\gamma_+ i_+(t) \\
\frac{di_+(t)}{dt} &= -i_+(t)c(1-\omega)f_-(n_-(t)) + i_-(t)c(1-\omega)f_+(n_+(t)) \\
&\quad + s_+\lambda_+(t) - \gamma_+ i_+(t) \\
\frac{dr_+(t)}{dt} &= -r_+(t)c(1-\omega)f_-(n_-(t)) + r_-(t)c(1-\omega)f_+(n_+(t)) \\
&\quad + (1-G)\gamma_+ i_+(t) \\
\frac{ds_-(t)}{dt} &= s_+(t)c(1-\omega)f_-(n_-(t)) - s_-(t)c(1-\omega)f_+(n_+(t)) \\
&\quad - s_-\lambda_-(t) + G\gamma_- i_-(t) \\
\frac{di_-(t)}{dt} &= i_+(t)c(1-\omega)f_-(n_-(t)) - i_-(t)c(1-\omega)f_+(n_+(t)) \\
&\quad + s_-\lambda_-(t) - \gamma_- i_-(t) \\
\frac{dr_-(t)}{dt} &= r_+(t)c(1-\omega)f_-(n_-(t)) - r_-(t)c(1-\omega)f_+(n_+(t)) \\
&\quad + (1-G)\gamma_- i_-(t),
\end{aligned} \tag{6}
$$

where

$$
G = \begin{cases} 1 \text{ for a SIS model,} \\ 0 \text{ for a SIR model,} \end{cases} \tag{7}
$$

and λ_+ and λ_- are specified by Eq. (2).

Acknowledgments

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Supplementary Material

Supplementary material is available at *PNAS Nexus* online.

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Authors' Contributions

M.E.K. and V.B. conceived the study and developed the model. M.E.K. and A.T. performed stability and bifurcation analysis of the model dynamics. A.T. implemented the model and carried out all numerical model analyses. A.T. prepared figures with input from V.B., H.N., and M.E.K. All authors participated in the discussion and interpretation of the outputs of the model. A.T. performed relevant literature overview. A.T. and M.E.K. wrote the manuscript. All authors contributed to editing of the final version of the manuscript, and gave the final approval for publication.

Model code

The model was implemented in MATLAB R2021b (60). The code producing the analyses and figures for this study is available at https://github.com/aiteslya/TwoOpinion (61).

Data Availability

No outside data was used to perform analyses in this study. The data necessary to produce figures in the manuscript is generated by the model code, which is contained in the shared repository.

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