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Article

Keywords: epidemic, metapopulation network model, medical resources

Posted Date: August 17th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-792903/v1>

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Intervention of resource allocation strategies on spatial spread of epidemic

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Abstract

Medical resources are crucial in mitigating the epidemic, especially during pandemics such as the ongoing COVID-19. Thereby, reasonable resource deployment inevitably plays a significant role in suppressing the epidemic under limited resources. When an epidemic breaks out, people can produce resources for self-protection, or donate resources to help others. That is, the exchange of resources also affects the transmission between individuals, thus, altering the epidemic dynamics. To understand factors on resource deployment and the interplay between resource and transmission we construct a metapopulation network model with resource allocation. Our results indicate actively or promptly donating resources is not helpful to suppress the epidemic under both homogeneous population distribution (HOD) and heterogeneous population distribution (HED). Besides, strengthening the speed of resource production can significantly increase the recovery rate so that reduce the final outbreak size. These results may provide policy guidance towards epidemic containment.

Introduction

Curbing the spread of epidemics is vital to human society today. During the past decades, human has experienced several major pandemics such as the Severe Acute Respiratory Syndrome (SARS) in 2003¹⁻³, the Middle East Respiratory Syndrome (MERS) in 2012^{4,5}, the western Africa Ebola⁶⁻⁸, and so on. Currently, the ongoing novel coronavirus disease (COVID-19) has diffused to almost every country in a short period of time, which has been characterized as a Public Health Emergency of International Concern (PHEIC) by WHO⁹⁻¹². With the increasing of new infected cases, there is an enormous demand for medical resources such as masks, protective clothes, ventilators, etc¹³. Some countries (regions, or cities) have excessively consumed medical resources because of curing massive infected cases, leading to healthcare systems being overwhelmed^{14,15}. Importantly, medical resources play a crucial role in curbing the epidemic, and greatly affect the spread process¹⁶. However, faced with the outbreak of the epidemic, it is necessary that countries (regions, or cities) produce medical resources for self-protection, as well as contributing/receiving resources to/from others cannot be ignored. Thus, there is an urgent need to better deploy limited medical resources to restrain the spread of epidemic.

The studies about the effects of medical resources on suppressing epidemic through network science are widespread¹⁷⁻²¹. Some studies have investigated how best to allocate the limited resources based on single layer networks^{22,23}. In addition, considering different effects such as information

diffusion and epidemic spreading, a number of studies have investigated the coevolution dynamics coupling resource allocation with multilayer networks²⁴⁻²⁷. But these studies are mainly carried out via contact networks in which nodes represent individuals and links denote the contacts between individuals. Nowadays, due to frequent spatial activities of humans and convenient traffic such as airline networks, epidemics especially COVID-19 can rapidly diffuse through the migration of population.

Metapopulation network model can be well used to investigate the spatial spread of epidemic due to the mobility of individuals²⁸⁻³³. In this framework, nodes represent subpopulations (e.g., regions, cities or countries), while links represent the migration routes between subpopulations. The infection occurs by the interaction of individuals within a subpopulation and the diffusion corresponds to their migration along the links between subpopulations, which is called reaction-diffusion (RD) process^{31,34,35}. Some studies have explored the effects such as mobility rate and non-uniform intervention for suppressing epidemic³⁶⁻³⁸, whereas factors such as medical resources inevitably playing the uttermost role in suppressing epidemic have been ignored. As the outbreak of COVID-19 in Wuhan, China, the government promptly deployed medical resources from other cities to Wuhan, and consequently controlled the epidemic. Hence, when facing an epidemic, deploying limited resources reasonably to locations plays a fundamental role in suppressing the epidemic.

Here, we construct a metapopulation network model with Migration-Interaction-Return (MIR) to investigate the coevolution dynamics of epidemic spreading and resource allocation (Fig. 1). Specifically, we model the spatial structure of realistic populations and the behavior of individuals in virtual social networks through a reaction-diffusion process based on the classical susceptible-infected-susceptible (SIS)³⁹ model. Besides, the microscopic Markov chain theory is applied to derive the epidemic threshold, and Monte Carlo (MC) simulation is used to verify the accuracy with the Markov equations.

Fig. 1 Schematic of the Migration-Interaction-Return (MIR) metapopulation network model with resource allocation. Firstly, local individuals may move to neighboring subpopulations along the links (solid arrow). Once individuals moved, they will react in a well-mixed way according to the SIS model. Susceptible individuals in subpopulation i get infected at rate $\lambda_i(t)$ while infected individuals get recovered at rate $\mu_i(t)$. The parameters $\lambda_i(t)$ and $\mu_i(t)$ dynamically change with time due to the exchange of resources between subpopulation i and its neighbors, $\omega_{i \rightarrow j}$ or $\omega_{j \rightarrow i}$ (dotted arrow). After reaction, they return to their resident subpopulations and the next time step starts.

Generally, infected individuals consume medical resources for treatment, while susceptible individuals are responsible for producing resources, e.g., face masks, ventilators, etc. Hence, the amount of resources produced by a subpopulation can be assumed proportional to the ratio of

susceptible individuals it contains. We designate a parameter $\theta (\geq 1)$ as resource production strength, and the parameter θ times the current subpopulation's fraction of susceptible individuals is regarded as productive resources in a time step. Apparently, a higher value of θ means a faster speed of resource production.

With the emergence of infected individuals, subpopulations can perceive the risk from neighbors. Usually, the more infected individuals emerge in a subpopulation, the more resources are supposed to be donated to it. In other words, the amount of resource donation of one subpopulation increases with the number of infected individuals that its neighboring subpopulations contain. In this paper, considering factors that may affect a subpopulation's donation will, we can summarize them as how many and when to donate resources, i.e., the donation awareness which restrains donating scale by considering the need for self-protection, and its response speed to donate resources, which is often related with the infected individuals surrounded with it. Therefore, we define the donation will mainly controlled by two parameters, i.e., $\alpha \in [0, 1]$ represents the subpopulation's resource donation awareness, and $\beta (\geq 0)$ describes the subpopulation's resource donation sensitivity, respectively (See Supplementary Information for details). The higher donation awareness means fewer resources can be donated, and the lower donation sensitivity means a larger initial donation will and a steady growth of it with the increasing of surrounded infected individuals, and vice versa. Differing from the classical contact networks, in which each node denotes an individual and resources are uniformly distributed to its infected neighbors. In our model, given that every subpopulation contains a crowd of individuals, the resources are allocated proportional to the degree that the neighboring subpopulations get infected. That is, a subpopulation with more serious infection would obtain more resources, which agrees with the current policy guidance of governments.

Without a doubt, after exchange of resources between subpopulations, the infection rate and the recovery rate will alter. Naturally, a subpopulation becomes risky to be infected after donating resources, while it is helpful for treatment when holding more resources. Thus, we can formulate the epidemiological process with the resource donation process. In other words, one subpopulation gets a higher infection rate when it donates resources to others. Instead, it gets a higher recover rate when holding more resources, i.e., it produces or receives more resources. In short, by producing and donating resources to infected subpopulations, the epidemic process is coevolved with the resource donation dynamics.

Results

To understand the coevolution process of resource donation dynamics and the epidemic dynamics, we systematically explore the impacts of resources donations, such as donation awareness α , donation sensitivity β , and resource production strength θ . We have performed an extensive set of stochastic simulations on the scale free (SF) networks with 1000 nodes, whose average degree is 6.9. The edge weights between nodes are uniformly distributed within the range of $[1, 50]$. Two types of population distributions, i.e., homogenous distribution (HOD), where each subpopulation contains the same number of individuals, and heterogeneous distribution (HED), where each subpopulation contains the number of individuals which is proportional to the sum of its edge weights, are considered respectively. Each subpopulation contains 100 individuals under HOD, and the total number of individuals is 100,000 under both HOD and HED. The microscopic Markov chain starts by infecting a small fraction of individuals as seeds in each subpopulation. Without loss of generality, 0.1% of individuals is set to be infected initially. Correspondingly, the same initial condition is applied to the Monte Carlo simulations, so each individual is set to be infected with probability 0.001.

Effects of the resource donation awareness on the epidemic spread

Fig. 2 The final epidemic prevalence ρ versus basic infection rate λ for various values of α . **a** Homogeneous population distribution (HOD), and **b** Heterogeneous population distribution (HED) (The inset shows the detail Markov process as λ between 0.001 and 0.002). The solid curves correspond to the iterations of the Markov equations (the color of each curve indicates the value of α as shown in the color bars), whereas the dots represent the results of Monte Carlo (MC) simulations. Each dot is the average over more than 50 MC simulations. The triangles under x-axis are the epidemic thresholds by the iteration of the Markov equations. The other parameters β and θ are set as $\beta=1$ and $\theta=1$.

To highlight the effects of each subpopulation's donation awareness α on the epidemic spreading, we set $\beta=1$ for the general donation sensitivity, and $\theta=1$ for the normal productive strength. Figure 2 shows the final prevalence ρ at steady state versus basic infection rate λ for various values of α under the conditions of HOD and HED, respectively (There is a perfect agreement between the iterations of Markov equations and Monte Carlo (MC) simulations). In addition, there is no resource exchange between subpopulations when $\alpha=1$, and full donation will when $\alpha=0$. From Fig. 2, the epidemic thresholds under HOD are overall higher than HED. Because under HED some subpopulations with

more population would have more infected cases initially, the epidemic easily breaks out and quickly spreads out by migration. But under HOD, the infected cases are uniformly distributed in each subpopulations initially, inducing a slower spreading with a higher epidemic threshold.

For the case of HOD, we see that lower awareness (smaller α) or stronger will of resource donation among subpopulations would promote the epidemic spread with a reduced epidemic threshold and a larger outbreak size. When an outbreak occurs in a subpopulation, neighboring subpopulations with high donation will would donate more resources to it, leading to high infection rates in them (Supplementary Fig. S2 (d), (e), and (f)). The dynamics of the donation will (Supplementary Fig. S2 (a)), as well as the infection ratio of neighboring subpopulations (Supplementary Fig. S2 (c)) for all the subpopulations in the networks are collected and support the results. It seems that actively donating resources to the infected subpopulation is not helpful to suppress the epidemic.

In contrast, for the case of HED, we can see that lower awareness (smaller α) or stronger will of donation among subpopulations would delay the outbreak of the epidemic with a higher epidemic threshold, but induce a larger final outbreak size. Because under HED the epidemic would easily break out in subpopulations with more population, a lower awareness indicates that neighboring subpopulation would donate more resources to it, leading to the containment of the epidemic (Supplementary Fig. S4). But a lower awareness also induces a larger outbreak size as previous situation. It suggests that actively donating resources just delays the outbreak at the early time, but is not helpful to suppress the epidemic while continuously donating resources.

Effects of the resource donation sensitivity on the epidemic spread

Fig. 3 The final epidemic prevalence ρ versus basic infection rate for various values of the donation sensitivity β . **a** Homogeneous population distribution (HOD), and **b** Heterogeneous population distribution (HED) (The inset shows the detail Markov process as λ between 0.001 and 0.002). The solid curves correspond to the iterations of the Markov equations (the color of each curve indicates the value of β as shown in the color bars), whereas the dots represent the results of Monte Carlo (MC) simulations. Each dot is the average over more than 50 MC simulations. The triangles under x-axis are the epidemic thresholds by iteration of the Markov equations. The other parameters α and θ are set as $\alpha=0$ and $\theta=1$.

In order to understand the impacts of the donation sensitivity β on the epidemic, we set $\alpha=0$ with no awareness namely full will of resource donation, and $\theta=1$ for the normal speed of resource production. Figure 3 shows the final prevalence ρ at steady state versus the basic infection rate λ

under various values of β (There is a perfect agreement between the iterations of the Markov equations and MC simulations). Particularly, the donation will be constant, i.e. 0.5, if $\beta=0$ (Supplementary Fig. S1). From Fig. 3, the epidemic thresholds under HOD are overall higher than HED.

Under the condition of HOD, we see that higher donation sensitivity (larger β) can delay the epidemic with a higher epidemic threshold, but induce a higher final break size. Because a larger β means a lower initial donation will (see Supplementary Fig. S1), neighboring subpopulations donate fewer resources when the epidemic breaks out in one subpopulation, leading to low infection rates in them (shown as Supplementary Fig. S5 (d), (e), and (f)). However, a larger β induces higher final outbreak size because the rapid growth of donation will lead to high infection rates in neighboring subpopulations (Supplementary Fig. S6 (d), (e), and (f)). It seems that donating resources or quickly response to the infected subpopulation would induce high infected scale instead.

Under the condition of HED, we can see that higher donation sensitivity (larger β) can promote the epidemic outbreak with a lower epidemic threshold and induces a larger final outbreak size. Because under HED the epidemic would easily break out in subpopulations with more population, they can receive more resources from neighbors to suppress the epidemic due to a higher initial donation will with a lower donation sensitivity (lower β), leading to a higher epidemic threshold (Supplementary Fig. S8). However, a larger β also induces higher final outbreak size as the rapid growth of donation will lead to high infection rates (Supplementary Fig. S7 (d), (e), and (f)). It suggests that donating a big amount of resources earlier just delays the epidemic, and promptly increasing resource donation is also not conducive to reduce final infected scale.

The coupling effects of donation awareness and donation sensitivity

Fig.4 The epidemic prevalence (color value) as a function of α and β by Monte Carlo (MC) simulations when close to threshold. a Homogeneous population distribution (HOD, $\lambda=0.00325$), and **b** Heterogeneous population distribution (HED, $\lambda=0.0015$). The white solid lines are corresponding thresholds of α and β .

To shed light on the interplay between the donation awareness α and donation sensitivity β , we plot the epidemic prevalence under the cases of HED and HOD respectively when close to threshold as shown in Fig.4. For the case of HOD, it shows that that high donation awareness and high donation sensitivity can delay the epidemic with a low prevalence, which clearly indicates that donating more resources (lower α) may promote the epidemic, and donating resources promptly (higher β) can validly suppress the epidemic. Therefore, these results indicate that we need to increase resource

202 donation steadily, avoiding donating a large amount of resources initially without protecting ourselves.
 203 Instead, under the case of HED, low donation awareness and low donation sensitivity can
 204 suppress the epidemic outbreak, which indicates that we need to immediately donate plenty of
 205 resources to infected subpopulations, especially with more population, to rapidly suppress the
 206 epidemic. But promptly increasing the resource donation (higher β) with the outbreak size is not a
 207 valid strategy.

208 Effects of the resource production strength on the epidemic spread

209
 210 **Fig. 5 The final epidemic prevalence ρ versus basic infection rate λ under various values of resource**
 211 **production strength θ .** **a** Homogeneous population distribution (HOD), and **b** Heterogeneous population
 212 distribution (HED). The solid curves correspond to the iterations of the Markov equations (the color of each curve
 213 indicates the value of θ as shown in the color bars), whereas the dots represent the results of Monte Carlo (MC)
 214 simulations. Each dot is the average over more than 50 MC simulations. The triangles under x-axis are the epidemic
 215 thresholds by iteration of the Markov equations. The other parameters α and β are set as $\alpha=0$ and $\beta=1$.

216 In the real world, individuals can recover to susceptible state by plenty of medical resources, so
 217 the more resources they hold, the higher recovery rate they get. The production strength θ is the
 218 parameter used to measure the ability of resource production in one time step. In order to interpret
 219 the impacts of production strength on the epidemic spread, we set $\alpha=0$ for no awareness namely full
 220 will of resource donation, and $\beta=1$ for the general donation sensitivity. Figure 5 shows the final
 221 epidemic prevalence ρ versus basic infection rate λ under various values of θ (There is a perfect
 222 agreement between the iterations of the Markov equations and MC simulations). It can be regarded
 223 as a normal speed of resource production for $\theta=1$, and higher speed when θ is greater than 1.

224 From Fig.5, we see that higher production strength (larger θ) delays the epidemic with a higher
 225 epidemic threshold and reduces final outbreak size under both HOD and HED. This is because
 226 subpopulations can produce more resources each time step so that they averagely hold more resources,
 227 which leads to higher recovery rates and lower effective infection rates (as Supplementary Fig. S9 (e)
 228 shown). In addition, in SF networks with a heterogeneous topology, since hub subpopulations
 229 generally have more population with more infected cases initially, the epidemic can easily break out
 230 with a lower threshold under HED (Fig. S10).

231 As a consequence, higher resource production strength can effectively delay the epidemic spread
 232 and reduce final infected ratio regardless of HOD and HED, but this effect is limited because the
 233 average recovery rate approaches to 1 if θ reaches 20 or greater. Therefore, properly reinforcing the

234 strength of resource production for suppressing is necessary.

235

236

Discussion

237 Facing with epidemics, especially pandemics such as COVID-19, medical resources
238 undoubtedly play a significant role in suppressing epidemics, so the reasonable deployment about
239 resources become an important issue that we need to further investigate. While most of the advances
240 previously described have been focused on capturing the resource deployment based on contact
241 networks, less attention has been paid on the metapopulation networks. Due to current convenient
242 traffic, the human interactions induce the spatial spreading of epidemics by individuals' movement
243 between regions (or cities, countries), which ignores the role of resource deployment on the so-called
244 metapopulation networks.

245 In this work, we construct a metapopulation network model to study the resource deployment
246 on epidemic evolution. The results indicate that properly donating resources can delay the epidemic
247 with a high epidemic threshold under heterogeneous population distribution, but actively or promptly
248 donating resources to the infected subpopulation is not helpful to suppress the epidemic regardless of
249 homogeneous or heterogeneous population distribution. Besides, strengthening the speed of resource
250 production can significantly increase the recovery rate so that reduce the final infection ratio.
251 Therefore, facing with the outbreak of the epidemic, we should not blindly help others while
252 neglecting self-protection. Meanwhile, strengthening the speed of resource production is an effective
253 measure, which can clearly increase recovery rate so that promote recovery of infected cases.

254 However, our current work inevitably has several limitations. First of all, we simply consider
255 that the amount of resources generated by one subpopulation is proportional to its ratio of susceptible
256 individuals. However, under heterogeneous population distribution, these subpopulations with more
257 population tend to generate more resources than those with fewer population, so we can further
258 consider the factor of individuals on resource production. Besides, we assume resources are produced
259 by each subpopulations itself, but ignore global resources that can be allocated to each one. The
260 generation and allocation patterns of resources are expected to be further explored and compared in
261 the future.

262

Acknowledgements

263 This work was supported by the National Key Research and Development Program of China
264 under Grant No.2017YFE0117500, the National Natural Science Foundation of China under Grant
265 No.91746203, the National Key Research and Development Program of China under Grant
266 No.2018YFB0704400, and the Natural Science Foundation of Shanghai under Grant
267 No.20ZR1419000.

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