UNDERSTANDING THE DIFFERENT OBJECTIVES OF INFORMATION AND THEIR MUTUAL IMPACT: MULTI-INFORMATION MODEL

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Abstract. In this article, we propose a new multi-information discrete-time model describing the dissemination of several pieces of information from one person to another, it can be shared word-to-mouth or in certain types of online environments such as Facebook, WhatsApp, and Twitter. First, we present the model and the different possible interactions between its compartments. Based on the fact that there is always a goal behind publishing information, in the modeling process, we distinguish between information that shares the same objective and information that shares a contrary objective, to study the effect of those pieces of information on the others. To do this, we divide the entire target population into three groups for each piece of information and consider the possible transition between these groups. Numerical simulations are carried out to illustrate these effects, and to study the sensitivity of the model on its parameters to identify the most influential parameter.

Keywords: information; dissemination; multi-information; mathematical model; sensitivity.

2010 AMS Subject Classification: 94A15, 97R50, 34H05

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1. INTRODUCTION

Newer communication technologies have increased the possibilities for how people can send and receive information. Social media are one such technology that has seen increased usage as an information source [1]. These several different communication channels are playing a greater role in our daily lives and provide a unique opportunity to gain valuable insight on information flow and social networking within a society [2]. As the penetration of smart phones in societies increases there is a large growth in the use of mobile phones. This trend is followed by the fast growth in use of online social networking services. As a result, people become more and more addicted to the fact of posting and sharing informations with each other in the most popular social media technologies. Giving as example, social networking sites, micro-blogging sites, wikis, online forums, and online blogs [3]. It has been revealed that about 2 billion people use the Internet every day and its services [4].

People use online social tools to gather information, share stories, and discuss concerns[1]. Nowadays, it has become easy to access user messages to a wide audience [5]. As a consequence, information overload has become an ubiquitous problem in modern society , for the reason that social media users and micro-bloggers receive an endless flow of information often at a rate far higher than their cognitive abilities to process the information [6] .

As a new communication paradigm, social media has promoted information dissemination in social networks . However, little research has focused on the relationship between emotions and information diffusion in a social media setting. This study examines, whether sentiment occurring in social media content is associated with a user's information sharing behavior. On twitter for instance, this research has found that emotionally charged twitter messages tend to be retweeted more often ,and more quickly compared to neutral ones . This is one of the main reasons why companies pay more attention to the analysis of sentiment related to their brands and products in social media [7]. Taking into consideration the great impact of emotions ,and sentiments in the virtual world, it can affect the credibility of the information shared in the context of computer-mediated communication [3].

As more people rely on social media for political, social, and business events, it is more susceptible to become a place for evildoers to use it to spread misinformation and rumors [8].

Therefore, users have the challenge to discern which piece of information is credible or not. They also need to find ways to assess the credibility of information. This problem becomes more important when the source of the information is not known to the consumer [9]. For this reason , evaluating the information honesty on social media platform has become an important issue for today information consumers, due to the lack of professional gatekeepers to monitor content[10].

In the contemporary blogosphere, blogger credibility has often been replaced with some emergent terms, such as "authenticity", "legitimacy", "transparency", "authority", or "passion". For instance, the level of authenticity in the communicated messages now decides the blogger's credibility, rather than the communicator himself. Additionally, the legitimacy of the blogger is enhanced by the personal passion and devotion to the communicated content bring out the legitimacy of the blogger [11]. Another factor that people may consider as a way of measuring someone's credibility is the number of followers. The fact of being followed by few people could led to lower judgments of expertise and trustworthiness [12] . Unfortunately, none of these criteria assure the truthfulness of the information spread on the internet.

Unsecured information a term that connects to the defining characteristic of rumor as information that is suspect because of its uncertain origins within a social system [13],the World Wide Web is a fruitful environment for the massive diffusion of unverified rumors,also allows for the rapid dissemination of conspiracy theories that often elicit rapidly [14]. Rumors has been recognized as one of the most important contributing factors to violence, prejudice, and discrimination. Yet despite its significance in exacerbating societal discord and mistrust, little systematic scholarly attention has been paid to the political origins and consequences of rumor [15].

Thus, sharing a false information has a serious impact on many fields of society, giving as example economics; in March 1991, false rumors circulated that Tropical Fantasy Soda was manufactured by the Ku-Klux-Klan and caused black men to become sterile; sales plumed 70%, delivery trucks were attacked, and vendors dropped the product [16]. Politics are also targeted by rumors for personal purposes , such as decreasing the probability of voting for a specific candidate [17] or encouraging negative campaigns; when these rumors are e-mailed

to friends and family they become more likely to be believed and shared with others and these patterns of circulation and belief exhibit strong political biases [18]. Concerning the health field , misinformation and rumors regarding COVID-19 are masking healthy behaviors (hand washing, social distancing etc.) and promoting erroneous practices that increase the spread of the virus and ultimately result in poor physical and mental health outcomes among individuals. An example of hazards attributable to improper health communication can be drawn from Nigeria, where the health officials found several cases of overdose of Chloroquine (a drug used to treat malarial parasite) after the news regarding the effectiveness of the drug for treating COVID-19 spawned in the social media [19, 20].

Rumor spreading resembles epidemics spread. Nevertheless ,there are three ideas that do link Virus and rumors very well. First, the idea of contagion is present in both processes, even though the definitions are different.Second is the idea that little changes have big effects on the population .In the case of influenza, it is possible for only a few coughs and sneezes to cause infection in many people.The same holds for rumors due to the fact that only a few people need to know the rumor in order to have rapid dissemination. The final similarity is that major events happen in a short amount of time. The potential for an outbreak to occur is present for both epidemics and rumors [21, 22].

Therefore, the creation of rumor models had been necessary in order to understand the information dissemination laws, a standard model of rumor spreading was introduced by Daley and Kendall, which is called DK model. In this one, it is assumed that there are a number of people in the network are categorized into three groups [23] .Ignorants (people who are ignorant of the rumor), spreaders (they actively spread the missinformation), and the stiflers (those who have heard the rumor , but no longer are interested in spreading it) [24]. This model created by Daley and Kendall in which there exists three classes assume two distinct attitudes among suceptibles and spreaders: passive and active. The passive people are those who do not have many contacts, and active people are defined to be those who have many contacts [25]. Afterwards, Maki and Thomson developed another classical MK model, which focused on the analysis of the rumor spreading based on mathematical theory via direct contact between spreaders and others. After that , more and more scholars paid attention to the spread of rumors [26]. Then, a new rumor

spreading model, Susceptible-Infected-Hibernator-Removed (SIHR) model, is developed. The model extends the classical Susceptible-Infected-Removed (SIR) rumor spreading model by adding a direct link from ignorants to stiflers and a new kind of people-Hibernators [27], this model incorporated the mechanisms of memory and forgetting [24].

To introduce the information transmission mechanism clearly, nodes in the network can have three states: ignorant, spreading and recovered. A node is ignorant if it is interested in the information but has not yet received it. Nodes that have possessed a copy of information and are willing to disseminate the information to others can be seen as spreading nodes. If a node is not interested in the information and not willing to disseminate it either, this node can be looked upon as a recovered node.Combined with three states of mobile nodes mentioned above, the detailed information dissemination process is introduced. Usually, mobile users may be willing to help their friends rather than anyone upon contact, which is a practical concern in the real world but ignored in most of existing works. In MSNs, we consider that there is only one node having the information initially, which is the spreading node. All of other nodes are interested in the information at first, and willing to receive the information. However, most of the nodes cannot maintain the same interest all along. Some ignorant nodes may lose the interest later, and refuse to receive it. In other words, an ignorant node can directly become a recovered node, which is called pre-immunity. In addition, a spreading node may stop dissemination when it encounters a recovered friend-node, which is called immunity. Moreover, spreading nodes may stop dissemination without any contacts due to their disinclination to deliver the information[28].

The fast exchanging of misinformation has been hard to be controlled especially with the huge number of the internet consumers, and perceived source credibility becomes an increasingly important variable to examine within social media, especially in terms of crisis and risk information. This is because of the increasing amount of information available through newer channels, the gatekeeping function seems to shift away from producers of content and onto consumers of that content [1]. Additionally, the problem of identifying rumors is of practical importance especially in online social networks, since information can diffuse more rapidly and widely than the offline counterpart, this unsecured information may affect a various fields of a

society. The credibility is required to keep the information trustworthiness and save the whole community from the negative impact of rumors.

Infectious disease modeling is a tool used to study disease spread mechanisms, predict the future course of an epidemic, and evaluate epidemic control strategies [23, 29, 30, 31, 32, 33, 34]. Epidemiological protocols have become an important raw material for disseminating information in networks [35]. Glaring examples of so-called diffusion protocols [36]. It is possible to apply mathematical models to collect information about disseminating ideas and information, thus allowing the testing of social hypotheses [37, 38, 21].

The similarities between the spread of the epidemic and the spread of information allowed the researcher to use epidemiological models to model information dissemination. In this article, we propose a new multi-information model, in-which we divide the population into three groups for each information, which will make it possible to study the development of ignorant people (people who do not know the information), spreaders (people who are interested in this information and who find pleasure in sharing it), removed (people who see that this information lacks relevance and compatibility with their profiles, then they refuse to share it). We study the impact of the model's parameters on the evolution of information by providing different numerical examples.

2. PRESENTATION OF THE MODEL

Information is easily spread, by all means, word of mouth, emails, phone calls, social networks, etc. With the help of all the advanced technologies that facilitate human communication, information spreads quickly. One of the most important factors in spreading information is the option of "Share" that accompanies any status update, link, video, or image posted. Content viewers (for example, friends of the creator and subscribers) are allowed to share the post. For example, on almost social networks, if the content was originally posted publicly, anyone can view and share it [21].

We devise here a compartmental model to study the dissemination of p information in an online environment of N users (Facebook, WhatsApp or Tweeter groups or pages) by posting, sharing and discussing. In these online environments, when a user posts information (text, image, video etc.), only his neighbors can see it and decide whether this information is worth

sharing again or not. If the information is very interesting and some neighbors decide to share it, the author's neighbors can see it and also re-share it. After that, the influence of the information goes beyond the local scope of the author and can be widely publicized on the network. On the other hand, if none of the original author's neighbors are attracted to this information, it will soon disappear and very few users will see it. At the same time, if neighbors see the message and do not immediately share it, they may gradually lose interest and ignore to share this information.

However, if the user notices that some information is being duplicated and shared by many of his neighbors, he will discuss it with his friends via chat tools or face to face, so that he can determine the relevance of this information and then decide to share it or not. When people debate a topic, they rely on a set of consistent information to validate their point of view, and thus persuade others who might have an opposing opinion. The aim of the discussion may not be to convince others of a dissenting opinion, but rather to persuade them not to publish more information that shows their point of view.

To incorporate all these considerations in our model, we assume that there are p information circulating on the internet, that is $\mathscr{J} = \left\{i_1, i_2, ..., i_p\right\}$ where $\mathscr{J}$ is the set of all these information. Usually we find several information that appear different, but the goal of publishing them is the same. For example, the information on the daily death toll from traffic accidents and the information on the number of daily traffic violations recorded, these information have the same goal, which is to improve driving by respecting the laws. While we can find other information that has the opposite purpose, for example information on traffic jams at a certain time or information on the application of quarantine from a certain time, these information may have the opposite purpose, which is to create a state of panic among the people and thus increase the violation of traffic laws.

Therefore, we suppose that information $z \in \mathscr{J}$ share the goal G_1, and the information $x \in \mathscr{J}$ share the goal G_2.

If $G_1 = G_2$, thus z and x are said media-compatible information.

If G_1 opposes G_2, thus z and x are said media-incompatible information.

If $G_1 \neq G_2$ and G_1 is not opposed to G_2, thus z and x are said media-independent information.

For an information $z \in \mathscr{J}$ we define the following sets:

$$C(z) = \{k \in \mathscr{J} / k \text{ and } z \text{ are media-compatible}\}$$

$$\bar{C}(z) = \{k \in \mathscr{J} / k \text{ and } z \text{ are media-incompatible}\}$$

$$N(z) = \{k \in \mathscr{J} / k \text{ and } z \text{ are media-independent}\}$$

Our model consists of three compartments of each information j: Ignorants, Sharers or spreaders, and Removed people. The term "ignorant" (I^j) means a person that does not know yet about the information j. The word "Sharer" (S^j) is used to denote that a person is attracted by the information j and/or he finds it funny or interesting, then he decides to share it. The term "Removed" (R^j) means a person who has seen and know about the information j and has decided not to share it. For example, because of irrelevance or for other personal reasons. We kept the term Removed from the classical SIR epidemiological model to denote individuals removed from the sharing system. All transmissions are modeled using the mass action principle, which accounts for the probability of transmission in contact between the different compartments.

Each information has the potential of sharing, but one can find some information not useful or does not fit the user interests, and then there is no need to share it. For example, if the information is about a concern of the public opinion (Raising costs of education, election cheats, public safety...), the probability of shares will be very important. Therefore, the potential relevance of the information will be taken into account and it will be defined based on the proportions of sharers. Let's define the potential relevance of the information j by the average β_j. After a contact between the ignorant I^j of the information j with a sharer S^k of the media-compatible information k (where $k \in C(j)$), the Ignorant I^j becomes a Sharer S^j just after he/she shares the information at the rate $\frac{\beta_k I_i^j S_i^k}{N_j}$, for $k \in C(j)$.

A sharer S^j of the information $j \in C(z)$ after a contact with a sharer S^k of the media-incompatible information $k \in \bar{C}(z)$ he/she would loss interest of sharing the information j and then become a removed of the information j at a rate $\frac{\alpha_j S_i^j S_i^k}{N_j}$. Note that $\frac{1}{\alpha_j}$ represents the power

FIGURE 1. Flow chart example for the model (1-3) with $\mathscr{J} = \{i_1, i_2, i_3\}$, where $C(i_1) = \{i_1, i_2\}$ and $\bar{C}(i_1) = \{i_3\}$.

$$C(i_1) = \{i_1, i_2\}$$ $$\overline{C}(i_1) = \{i_3\}$$
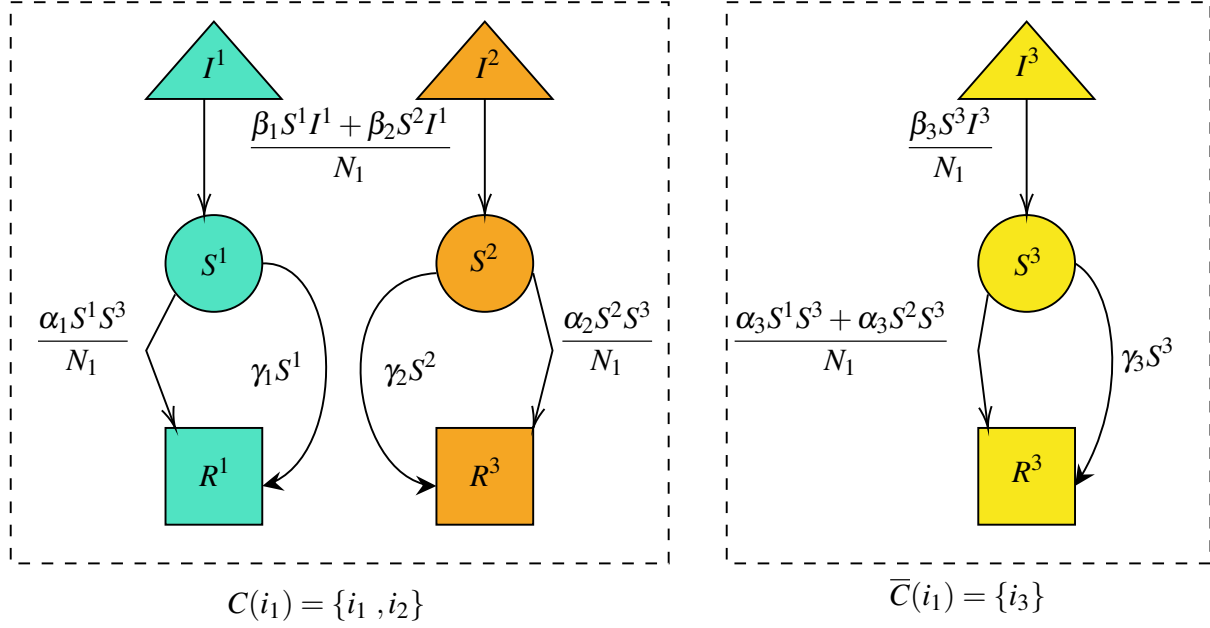
of persuading people by the information j and the ease with which it is accepted: the smaller α_j, the greater the strength of the information j.

Any sharer S^j can lose interest of sharing and decide at any time not to share the information j anymore for personal or other reasons, thus he becomes a Removed R^j at a rate $\gamma_j S^j$. All these interactions happen at the instant i, and N_i^j is the total targeted population by the information j at instant i, that this $N_i^j = I_i^j + S_i^j + R_i^j$.

We propose a discrete-time compartmental model describing the interactions between the different information governed by the following equations:

$$(1) \qquad I_{i+1}^j = I_i^j - \sum_{k \in C(j)} \frac{\beta_k I_i^j S_i^k}{N_j}$$

$$(2) \qquad S_{i+1}^j = S_i^j + \sum_{k \in C(j)} \frac{\beta_k I_i^j S_i^k}{N_j} - \sum_{k \in \bar{C}(j)} \frac{\alpha_j S_i^j S_i^k}{N_j} - \gamma_j S_i^j$$

$$(3) \qquad R_{i+1}^j = R_i^j + \gamma_j S_i^j + \sum_{k \in \bar{C}(j)} \frac{\alpha_j S_i^j S_i^k}{N_j}$$

Parameter	Description	Value for i_1	Value for i_2	Value for i_3	Value for i_3
I_0	Initial ignorant population	1×10^6	1090100	1050500	1×10^6
S_0	Initial sharer population	1000	100	100	100
R_0	Initial removed population	100	100	100	100
β	Rate of transition from ignorant to sharer	0.0292	0.0192	0.0232	0.0112
γ	sharing loss interest rate	0.0001	0.0004	0.0002	0.0006
α	Rate of convincing sharer of the opposite opinion	0.004	0.044	0.0004	0.0014

TABLE 1. Parameters description and values utilized for the resolution of the discrete system (1-3), and then leading to simulations obtained from Figure 2 to Figure 11, with the initial conditions I_0, S_0, R_0.

Where $S_0^j > 0$, $I_0^j > 0$ and $R_0^j > 0$, and $j \in \mathscr{J}$. Note that

$$N_{i+1}^j = I_{i+1}^j + S_{i+1}^j + R_{i+1}^j = N_i^j = I_0^j + S_0^j + R_0^j = N_j$$

.

A flow chart example for the model is shown in Fig. 1, and parameters description can be found in Table 1.

3. NUMERICAL SIMULATIONS

We now present numerical simulations associated with the above-mentioned model. We write code in MATLAB^{TM} and simulated our results using data from Table 1.

In these simulations, without loss of generality, we suppose that there are 4 different information, that is $\mathscr{J} = \{i_1, i_2, i_3, i_4\}$, and

$$C(i_1) = \{i_1, i_2\}$$

$$\bar{C}(i_1) = \{i_3, i_4\}$$

Which means that information i_1 and i_2 have the same objective O_1, i_3 and i_4 have the same objective O_2, where O_1 opposes O_2.

In all the simulations bellow, the hours were used as a time unit. Because the spread of information occurs faster in time. We focus here on information that is more appealing and has the potential to be shared. We have chosen as a studied population, a group (In Facebook,

Tweeter, WhatsApp etc.) with about more than 3000000 members, that can be considered as the ignorant group, about 1300 sharer, and about 400 removeds, at the initial time $i = 0$.

All parameters of the table 1 are chosen to get a situation in which the number of sharers rises above 10000 individuals of the population and the removed group remains small except the ones of the information i_1 which exceeds 5 millions at the end of this simulation.

In Fig.2 it can be seen that about 100 hour from the injection of the information, there is no more ignorant of the information i_1. Which means that the information reaches almost all the members of the group. We talk then about an explosion of the information i_1. In the case of false information, this situation can lead to serious economic and/or political damages. Because it can be seen from this figure that the more the number of sharers is big the more of the amount of the information is huge. Thus, the proliferation of information can not be stopped, consequently, it can spread out to external groups and reaches other spreaders in other environments.

The reason behind the increase in the population removed from the information i_1 is that the information has already reached all the ignorant members of the group and may have reached other groups resulting in a loss of interest in sharing this information.

It can be seen that the group $C(i_1)$ is dominant by the number of its participants, thus, we can expect that target O_1 attract more people, and hence it can easily eliminate the opposite opinion O_2 by reducing the number of participants in information i_3 and i_4. Where, we can see that the numbers of information participants i_3 and i_4 retain small values that do not exceed 4000 individuals compared to the number of information participants i_1 and i_2 which amount to 14000 individuals.

To evaluate the impact of each parameters of the model, we plot the different states of the model for several parameters' values. In figures 3, 4, and 5 we chose four different values of the parameter β_1, 0.0192, 0.0292, 0.0392, and 0.0492.

Fig. 3 shows the impact of the parameter β_1 on the ignorant populations. It can be seen from that figure that the parameter β_1 has a great impact on the evolution of the ignorant population of information i_1 and i_2, see sub-figures (a) and (b). While it has a small impact on the ignorant of the opposite opinion, see sub-figures (c) and (d). The greater the values of β_1, the faster the decrease in the ignorant populations. β_1 has a small positive impact on ignorant groups of the

FIGURE 2. Dynamic of the system (1-3): (a) Ignorants, (b) Sharers, and (c) Removeds.
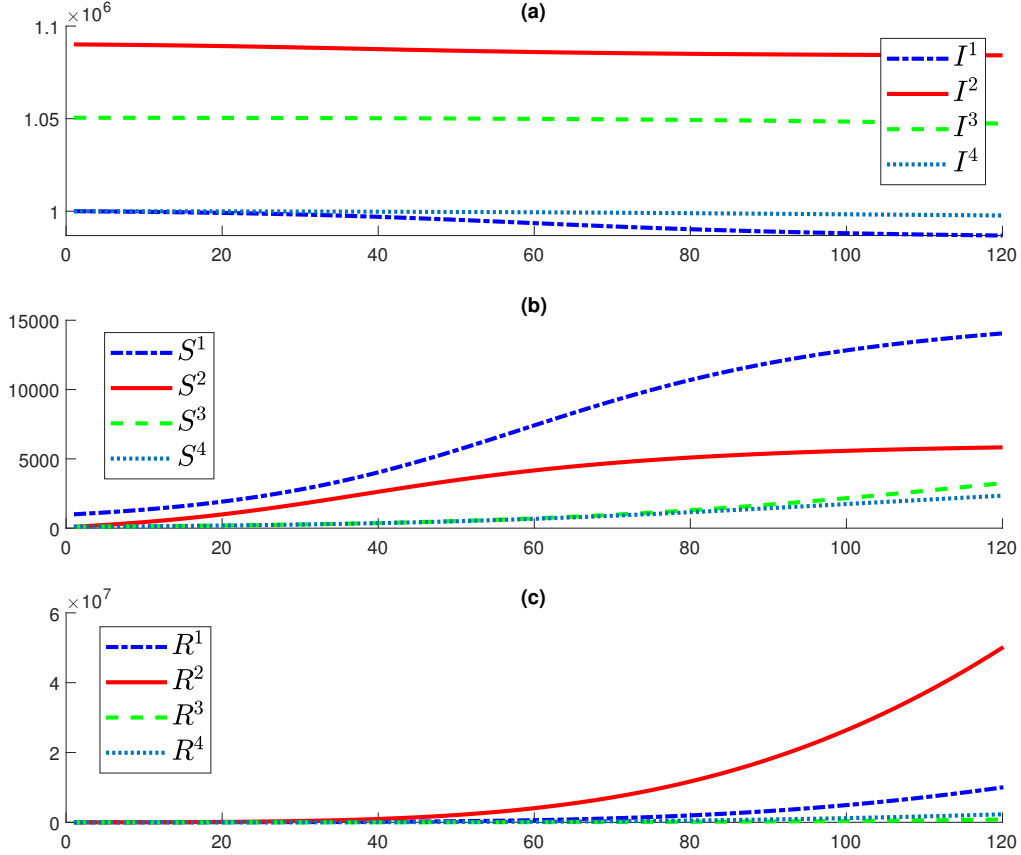

media-incompatible information and a big negative impact on the ignorant populations of the media-compatible information.

Fig. 4 shows the impact of the parameter β_1 on the sharer populations. We can see from that figure that the parameter β_1 has a great impact on the evolution of the sharer populations of information i_1 and i_2, see sub-figures (a) and (b). While it has a small impact on the sharers of the opposite opinion, see sub-figures (c) and (d). The greater the values of β_1, the faster the increase in the sharer populations of i_1 and i_2, and the greater the values of β_1, the smaller values in the sharer populations of i_3 and i_4. We can say that parameter β_1 has a negative effect on the sharer populations of the opposite opinion information.

Fig. 5 shows the impact of the parameter β_1 on the removed populations. We can see from that figure that the parameter β_1 has almost the same impact on the evolution of the removed

FIGURE 3. Impact of the parameter β_1 on the dynamic of Ignorant populations. (a) Ignorant of the information i_1. (b) Ignorant of the information i_2. (c) Ignorant of the information i_3. (d) Ignorant of the information i_4.
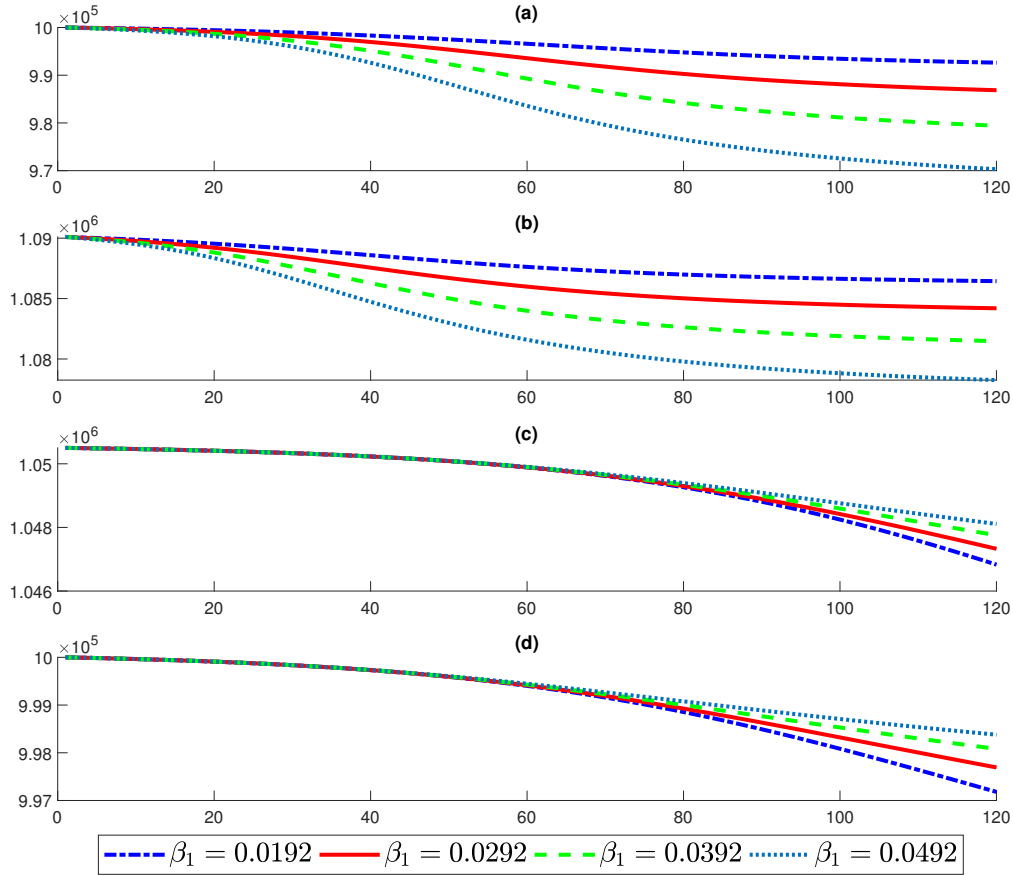
populations of all information i_1, i_2, i_3, and i_4. The greater the values of β_1, the faster the increase in the removed populations of all information. We can say that the parameter β_1 has a neutral impact on the removed populations of the opposite opinion.

In figures 6, 7, and 8 we chose four different values of the parameter γ_1, 0.0001, 0.001, 0.002, and 0.003. While the Fig. 6 shows the impact of the parameter γ_1 on the ignorant populations. We can see from this figure that the parameter γ_1 has virtually no effect on the development of the ignorant groups for all information i_1, i_2, i_3, and i_4. We can say that the parameter γ_1 has a no impact on the ignoring populations of all opinions.

FIGURE 4. Impact of the parameter β_1 on the dynamic of Sharer populations. (a) Sharers of the information i_1. (b) Sharers of the information i_2. (c) Sharers of the information i_3. (d) Sharers of the information i_4.
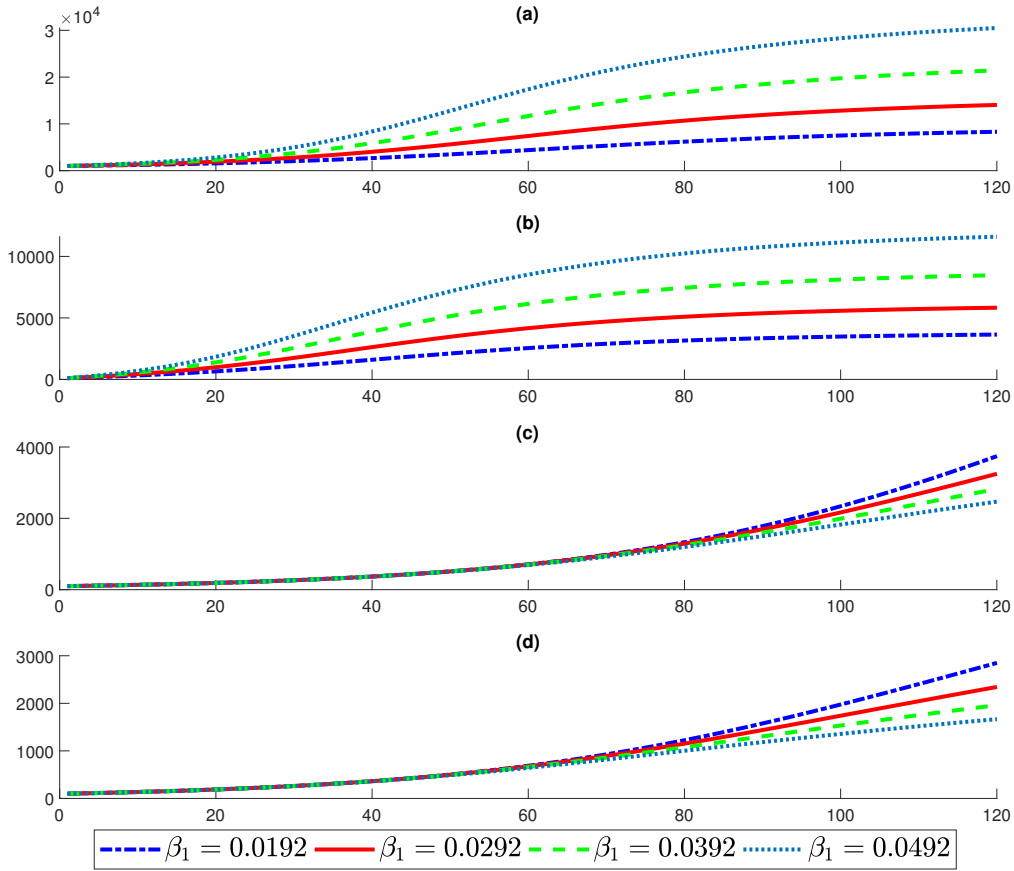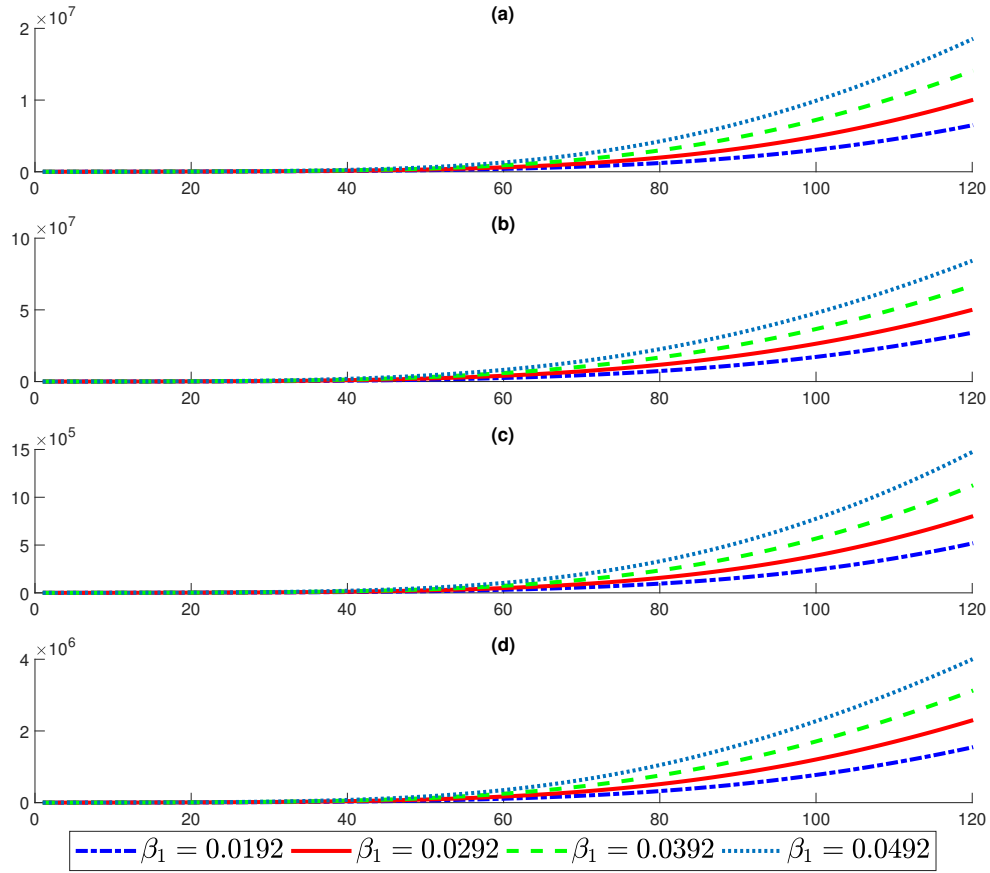

Fig. 7 shows the impact of the parameter γ_1 on the sharer populations. It can be seen from this figure that the parameter γ_1 has a remarkable effect on the evolution of the sharer group for the corresponding information i_1, moderate effect on sharers of media-compatible information in $C(i_1)$, and almost no effect on all information in the opposite opinion. We can say that the parameter γ_1 has a no impact on the sharer populations of the opposite opinion.

While Fig. 8 shows the impact of the parameter γ_1 on the removed populations. It can be seen from this figure that the parameter γ_1 has a moderate effect on the removed population of the corresponding information i_1, and removed populations of all media-incompatible information

FIGURE 5. Impact of the parameter β_1 on the dynamic of Removed populations. (a) Removed of the information i_1. (b) Removed of the information i_2. (c) Removed of the information i_3. (d) Removed of the information i_4.

in $\bar{C}(i_1)$, while it has no effect on the removed group of the media-compatible information in $C(i_1)$.

In figures 9, 10, and 11 we chose four different values of the parameter α_1, 0.0004, 0.001, 0.0018, and 0.0029. The Fig.9 shows the impact of the parameter α_1 on the ignorant populations. We can see from this figure that the parameter α_1 has a remarkable effect on the ignoring population of the corresponding information i_1, and a moderate impact on the ignorant populations of other information. Note that α_1 has a positive impact on the corresponding information and its media-compatible information $C(i_1)$, and a negative impact on information of the opposite opinion $\bar{C}(i_1)$.
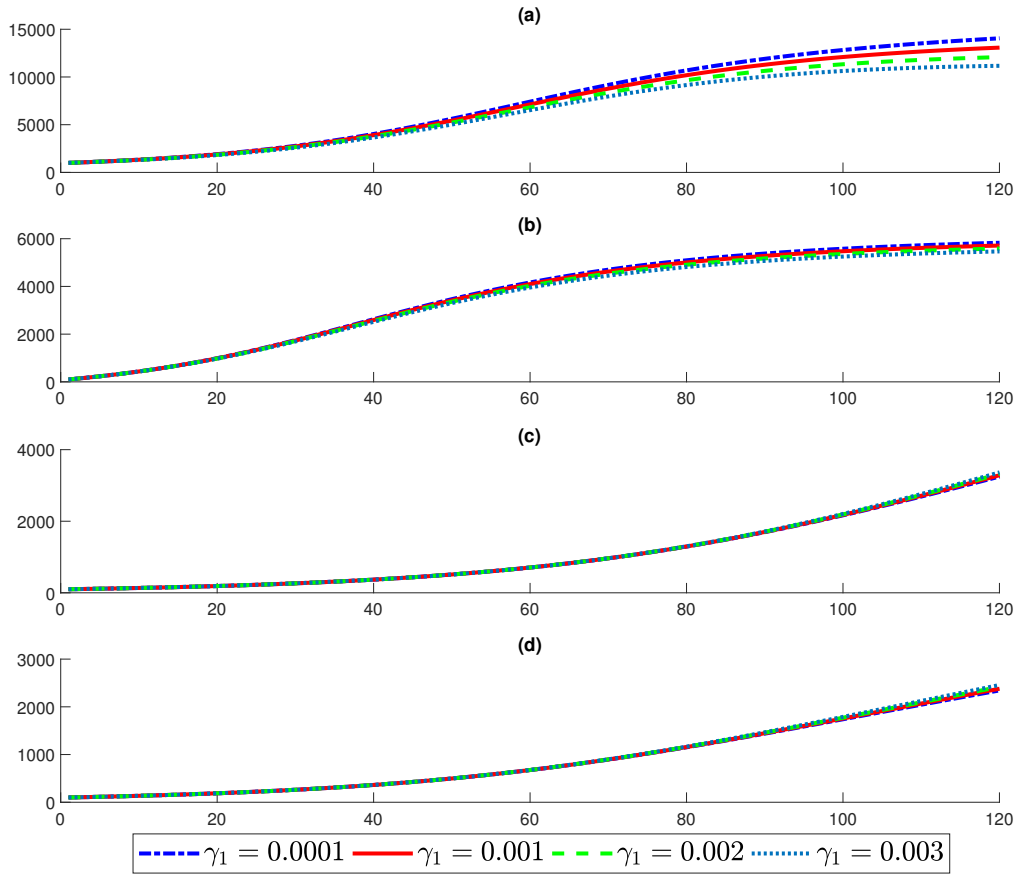
FIGURE 6. Impact of the parameter γ_1 on the dynamic of Ignorant populations.
(a) Ignorant of the information i_1. (b) Ignorant of the information i_2. (c) Ignorant of the information i_3. (d) Ignorant of the information i_4.
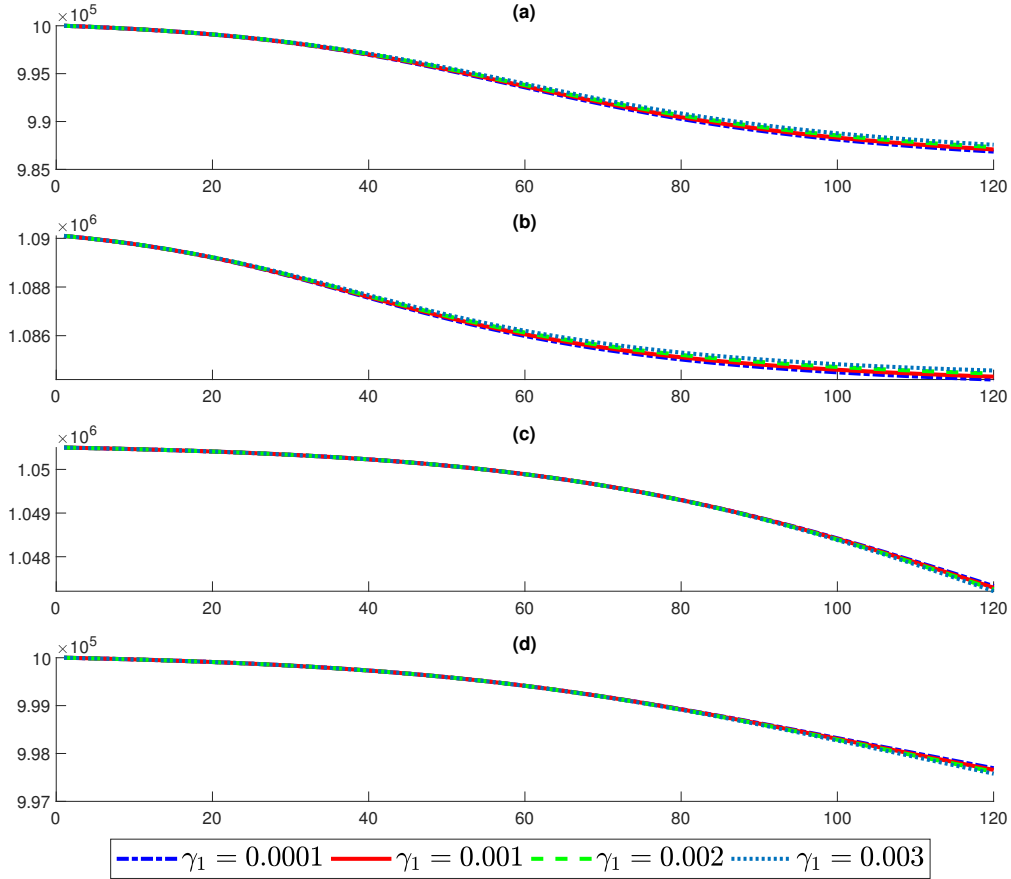
The Fig.10 shows the impact of the parameter α_1 on the sharer populations. Where we can see that the parameter α_1 has a remarkable effect on the sharer population of the corresponding information i_1, and a moderate impact on sharers of other information. Note that α_1 and the number of media-compatible information sharers S^1 and S^2 tend to very in a negative way, that is the higher the values of α_1, the fewer participants S^1 and S^2. We can say that the parameter α_1 has a negative impact on sharers of the corresponding information i_1 and its media compatible information.

While Fig.11 shows the impact of the parameter α_1 on the removed populations. Where we can see that the parameter α_1 has a remarkable positive effect on the removed population of

FIGURE 7. Impact of the parameter γ_1 on the dynamic of Sharer populations. (a) Sharer of the information i_1. (b) Sharer of the information i_2. (c) Sharer of the information i_3. (d) Sharer of the information i_4.

the corresponding information i_1, and a negative impact on its media-incompatible information $\bar{C}(i_1)$, while it has no effect on the removed group of the media-compatible information. The higher the values of α_1, the higher number of removed R^1.

FIGURE 8. Impact of the parameter γ_1 on the dynamic of Removed populations. (a) Removed of the information i_1. (b) Removed of the information i_2. (c) Removed of the information i_3. (d) Removed of the information i_4.
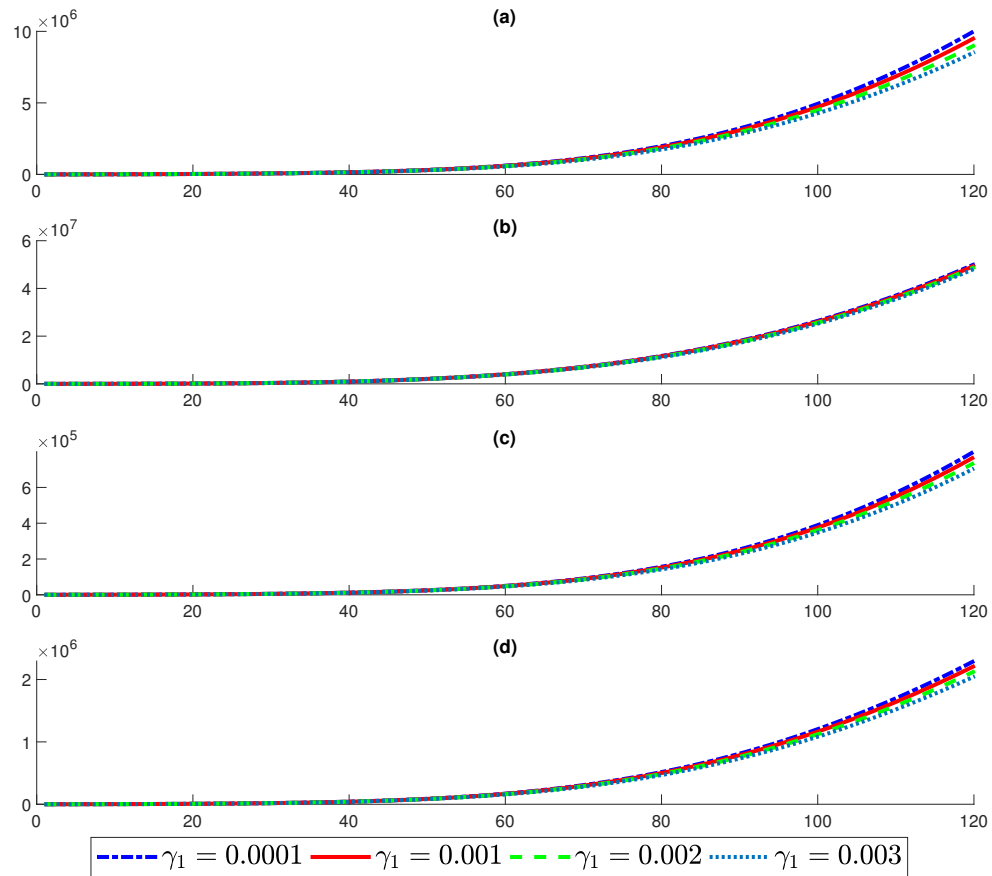
FIGURE 9. Impact of the parameter α_1 on the dynamic of Ignorant populations. (a) Ignorant of the information i_1. (b) Ignorant of the information i_2. (c) Ignorant of the information i_3. (d) Ignorant of the information i_4.
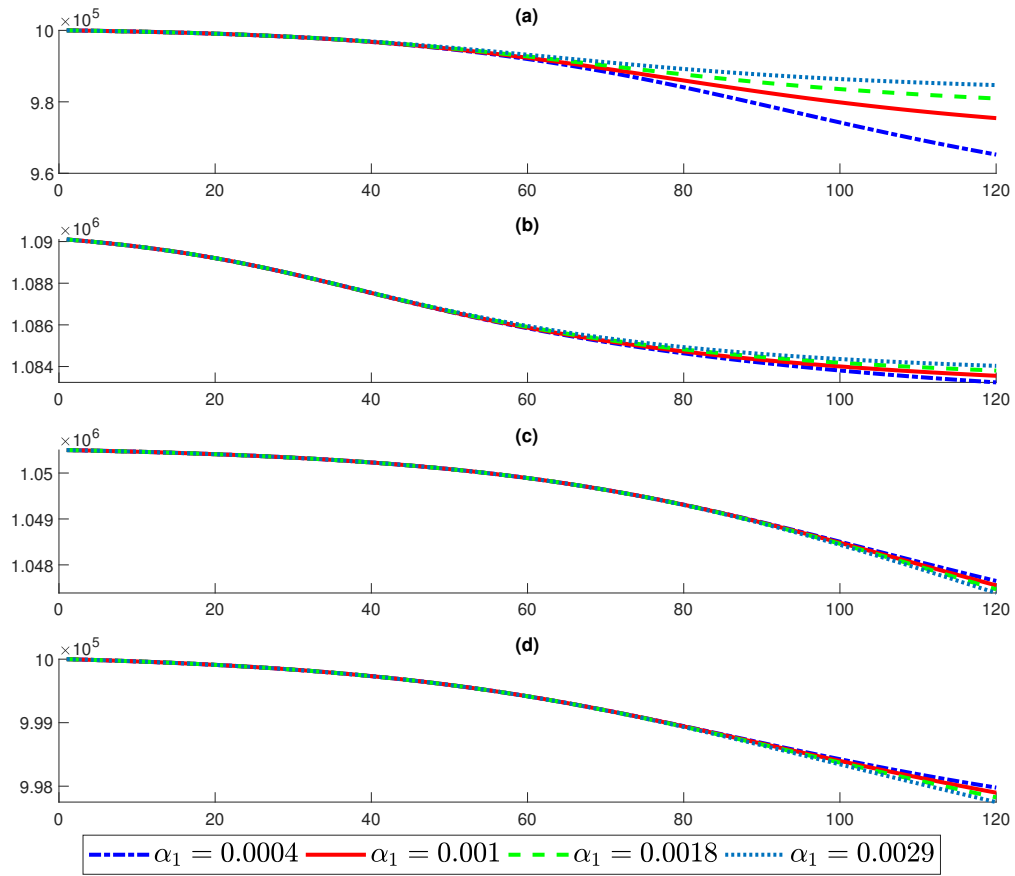
FIGURE 10. Impact of the parameter α_1 on the dynamic of Sharer populations. (a) Sharer of the information i_1. (b) Sharer of the information i_2. (c) Sharer of the information i_3. (d) Sharer of the information i_4.
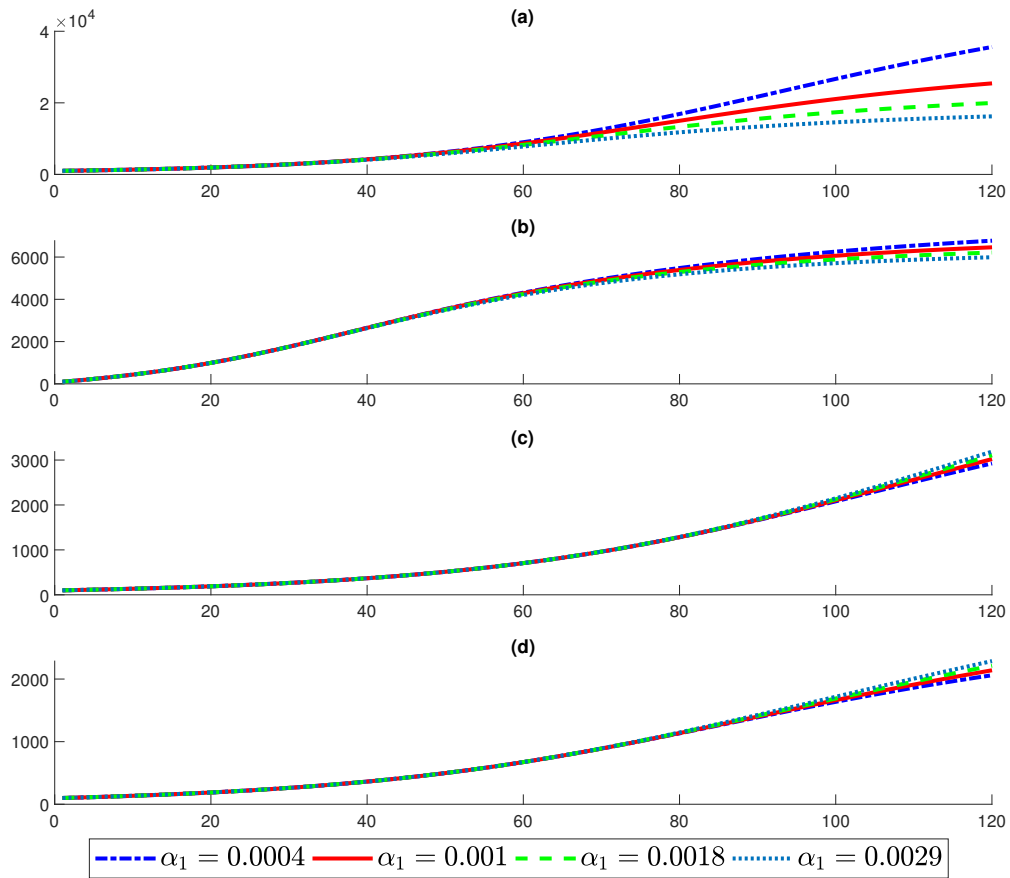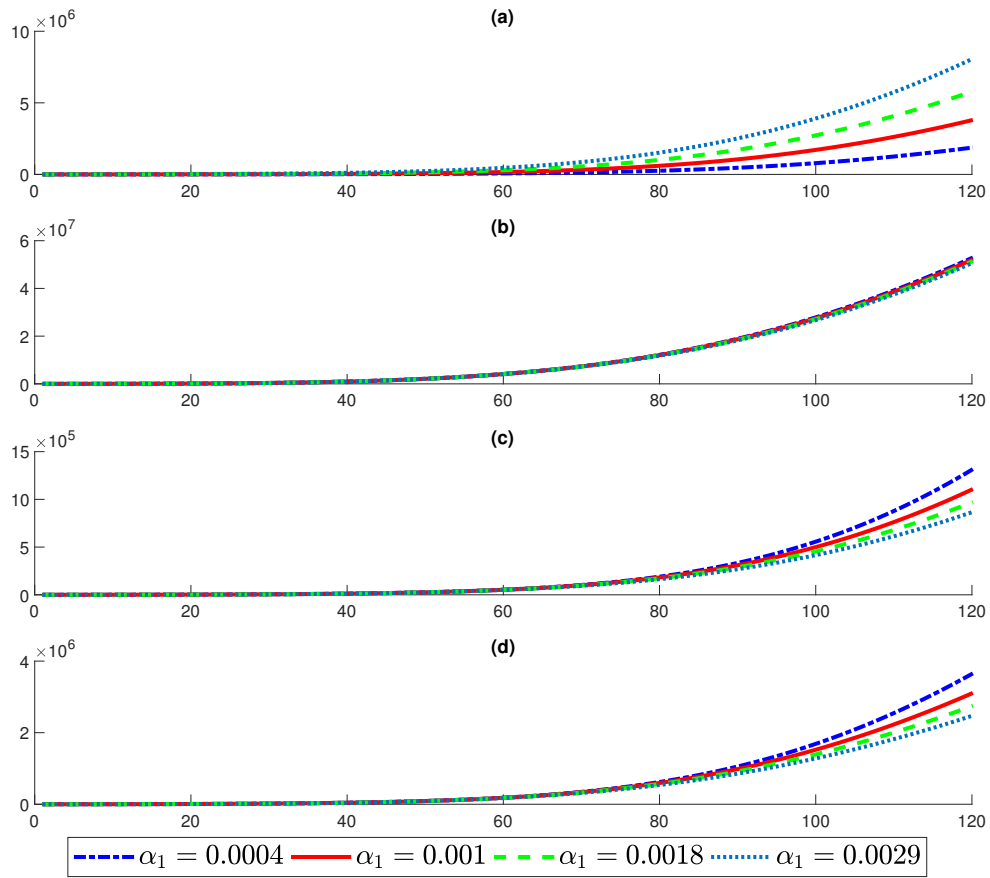
FIGURE 11. Impact of the parameter α_1 on the dynamic of Removed populations. (a) Removed of the information i_1. (b) Removed of the information i_2. (c) Removed of the information i_3. (d) Removed of the information i_4.

4. CONCLUSION

In this article, we proposed a new multi-information discrete-time model to describe the dissemination of several information from one person to another, it can be shared word-to-mouth or in certain types of online environments such as Facebook, WhatsApp and Twitter. We presented the new model and the different possible interactions between its compartments. We have assumed that the information set is composed of three subsets, information sharing an objective O_1, information sharing the opposite objective O_2, and neutral information.

We provided several examples to study the sensitivity analysis of the model to its parameters. We found that the transmission parameter of an information i_1 has a negative effect on the sharer populations of the opposite opinion information in $\bar{C}(i_1)$, and a neutral impact on the removed populations of the opposite opinion, while it has a small positive impact on ignorant groups of the media-incompatible information $\bar{C}(i_1)$ and a big negative impact on the ignorant populations of the media-compatible information. The loss of interest parameter has no remarkable effect on the development of all the groups. While the parameter α_1 has a remarkable effect on the ignorant population of the corresponding information i_1, and a moderate impact on the ignorant populations of other information. And it has a negative impact on sharers of the corresponding information i_1 and its media compatible information. α_1 has a remarkable positive effect on the removed population of the corresponding information i_1, and a negative impact on its media-incompatible information $\bar{C}(i_1)$, while it has no effect on the removed group of the media-compatible information.

CONFLICT OF INTERESTS

The author(s) declare that there is no conflict of interests.

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