

Harnessing the power of crowdsourcing and Internet of Things in disaster response

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Abstract Crowdsourcing and Internet of Things (IoT) are gaining more and more attention both in industry and academia in order to explore their effects on disaster relief. The current state of the literature shows a clear focus on the extent to which crowdsourcing on one hand, or IoT on the other hand, can individually make a difference regarding disaster response, but very few studies have considered the integration of both crowdsourcing and internet of things in order to link them with disaster response. Accordingly, in this paper, the authors have attempted to develop a crowdsourcing and IoT integration model which could help improving disaster response by using important value derived from using both social media and RFID technology. Furthermore, despite the fact that disaster relief offers similarities with epidemic transmission, (especially the SIR model), the application of SIR model in disaster relief still remains unexplored, which has led the authors to conduct a series of SIR model-based simulations to investigate the extent to which such integration model helps improving disaster response.

Keywords Crowdsourcing · Internet of Things (IoT) · Data analysis · SIR model · Disaster relief · Simulation

1 Introduction

Disasters cause human losses on a regular basis, and the crucial need for improving disaster response both effectively and efficiently has led to multiple studies in this field (e.g., Burkart et al. 2017; Yang et al. 2016; Duhamel et al. 2016; Wang et al. 2016; Xiang and Zhuang 2016; Yadavalli et al. 2015; Jin et al. 2015; Lei et al. 2015; Analya-Arenas et al. 2014; Paul

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and Hariharan 2012; Ozdamar et al. 2004). In a similar fashion that computers have changed the way we work and entertain, or smartphones have changed the way we communicate, the development of science and technology help changing the way we respond to disasters. Both crowdsourcing and IoT have individually contributed to the improvement of disaster response. On one hand, crowdsourcing, for instance, can transform—under specific circumstances—distant search into local search which enables companies to obtain many benefits of local search at a lower cost (Afuah and Tucci 2012). On the other hand, IoT is widely used in many fields (e.g., transportation and manufacturing) to create intelligent transportation systems where transportation authorities are able to track current locations of vehicles, monitor movements of vehicles, and predict future locations and possible road traffic. Overall, crowdsourcing and IoT have shown their respective individual impacts on disaster response, but their combined impact requires further investigation, which is at stake in this paper.

In order to further develop our relief model built on both crowdsourcing and IoT, we have taken into account the epidemic model which had been originally developed to discover the mechanism of disease transmission over the twentieth century. Since its inception, the epidemic model has been applied in many fields (e.g., economics, finance, and information transmission in social networks) with various studies demonstrating significant achievements. However, the application of this epidemic model in disaster relief still remains unexplored. Accordingly, this paper investigates a relief model integrating crowdsourcing, IoT, and the epidemic model all together.

Following this introduction, the paper is organized as follows. A brief review of the related literatures is presented in Sect. 2. Next, we summarize the key elements of our model and some dimension affecting the implementation of our model. In Sect. 4, we conduct a series of simulations to prove the feasibility of our model. The conclusion is summarized in Sect. 5.

2 Literature review

2.1 Crowdsourcing and IoT

The concept of crowdsourcing was firstly introduced by Howe (2006). Social media provides a significant example of crowdsourcing where, given the extensive use of social media nowadays across the globe, there are large amounts of User Generated Contents (UGC)—available on social media (e.g., Twitter, Facebook)—whose valuable information is extensively analyzed and used: such crowdsourcing is defined as passive crowdsourcing. Another case of passive crowdsourcing occurs when government agencies rely on social media to collect citizens' information about their respective knowledge, ideas and opinions about topics in order to use such information for policy making (Charalabidis et al. 2014). In a similar note, the power of social media in disaster relief cannot be ignored in the disaster-affected area because posted User Generated Contents may provide valuable information for disaster response which might remain unexploited. Moreover, analysing disaster-related UGCs is very challenging given such contents are primarily composed of text data and always carry many noises. In our paper, we focus on geographical information hidden in disaster-related data because geographical information is highly valuable in disaster relief: identifying the locations of victims from disasters leads to a more accurate rescue.

The concept of Internet of Things (IoT) was firstly introduced by Ashton (1999). In IoT, the Internet is an outspread conception of World Wide Web and it's the core base of the IoT. Things refers to connections between all types of things. The concept of Internet of Things

(IoT) goes usually with Radio-Frequency Identification Device (RFID) (Georgakopoulos and Jayaraman 2016). With RFID technology, people can do particular things they cannot when they don't have RFID. In disaster relief, when people obtain RFID equipment, they can also accomplish things they cannot before. For example, people in the disaster-affected area can use RFID to connect and help other people within a certain radius. Such form of assistance is quite necessary in disaster relief. When talking about IoT, another issue that cannot be neglected is people's acceptance of IoT. This problem has been paid a lot of attention since the introduction of IoT. It is indispensable to consider this issue especially when we apply IoT in disaster relief, where less mistakes can be tolerated.

Literature about the role of crowdsourcing on disaster relief exists on one hand, as well as literature on Internet of Things (Ng and Wakenshaw 2017) on the other hand, but research studies dealing with the integration of both is still underdeveloped, and more precisely their combined roles in disaster response. Regarding the combined roles of crowdsourcing and Internet of Things, Lambrinos (2015) argues that throughout an emergency, agencies firstly try their best to gather the information as much as possible to prepare for their relief, but, the process was very time-consuming such that they might miss the best time. Fortunately, they believe that today's ubiquitous connectivity between diverse devices is a perfect information source which can be used for emergency management. Some vital information from IoT-based system or an information-sharing mechanism of crowdsourcing such as location and images can be exploited accurately and timely to drastically improve the assistance efficiency. Rauniyar et al. (2016) hold that fog computing is more superior and faster than cloud computing when processing crowdsourced data such that the best opportunity to act on it could be seized. They therefore propose a Crowdsourcing-based Disaster Management using Fog Computing (CDMFC) model in IoT and a data offloading mechanism for CDMFC model which are able to detect real-time disasters and disseminate early information for public safety as compared to the conventional cloud computing based disaster management models. Dubey et al. (2015) used a two-prong research strategies: literature review and case studies to analyze the enablers of crowdsourcing and IoT respectively which can guide disaster response. They further propose a CS-IoT model based on the analysis using three case studies. The authors argue that crowdsourcing and internet of things can be integrated to improve disaster response, as long as their enablers are well exploited.

2.2 Big data analytics in disaster

Social media applies in many fields which can be viewed as a form of crowdsourcing: anyone can participate and be part of some programs. Users themselves may even not notice that they have already been a part of the crowdsourcing. Users use social media every day, which will generate countless data, which are both valuable and vital under certain circumstances.

Various studies have pointed out the extent to which social media provides values. First, Middleton et al. (2014) have developed an effective social media crisis mapping platform using real-time Twitter data to map natural disaster, which has proven to have high precision (90% or higher) compared to expert post-event assessment. Second, Imran et al. (2014) have shown that processing messages created by social media in emergency is very challenging including handling information overload, filtering credible information, and prioritizing different classes of messages. They therefore surveyed the cutting-edge computational methods to do these jobs, focusing on their application in emergency response scenarios. Third, Xu et al. (2017) believe that internet is becoming an important information provider when faced with emergency events and there is no doubt that these information is valuable in dealing with the events. However, it is extremely difficult to be processed because the resources are

huge, disordered and continuous. They therefore propose a crowdsourcing based burst computation algorithm to solve this problem. Fourth, Zook et al. (2010) have conducted a case study of the Haitian earthquake, which suggests that volunteered geographic information and crowdsourcing are important for web-based mapping services. Haiti is a very poor country with the lack of some key infrastructures and this dilemma offered huge challenges for disaster relief. Different to the existing works, this article emphasizes how people from different places around the world can cooperate together (via structures like CrisisCommons) to provide assistance when disaster happens. Fifth, these studies mostly focus on a macro level. For example, Dubey et al. (2015) analyze the enablers of crowdsourcing and IoT respectively which can guide disaster response and further propose a CS-IoT model. Overall, previous studies have explored the potential roles of crowdsourcing and IoT in the context of disaster response.

3 The relief model

Currently, the state of the academic literature indicates that studies have focused on the potential roles of crowdsourcing on one hand, as well as the potential roles of IoT on the other hand. The relief model we consider here investigates the roles of crowdsourcing and IoT all together.

The relief model we develop in this paper aims at answering the following research question: how can a model integrating both crowdsourcing and IoT be literally used in disaster? In order to so, the purpose is to figure out the applications of the proposed model in the real-world settings, i.e. we need to do it from a practical standpoint rather than a theoretical one.

In the following section, we will further explore the enablers of our model based on three dimensions, namely the technological, behavioral, and responsive dimensions.

3.1 Technological dimension

Regarding the technological dimension of our model, we take into account based social media and IoT devices. We discuss each of these two technologies in the next paragraphs.

3.1.1 Crowdsourcing based social media

In the information age, the social media has nearly become the necessity everyone needs in the daily life. Even though the introduction of social media is meant to connect people at different places in the first place, the meaning of the social media is way beyond that nowadays.

What draws our eyes is that users can post blogs at any place and any time about their life, the contents of which are often geo-tagged such that other users of the social media could see where users posting are.

We have a strong reason to believe that these volunteered geographic information can make a significant difference. If there is a victim in a disaster area, the victim will send out the message asking for help in all probability as long as he/she has access to such kind of device. In a catastrophe, such as flood, earthquake, hurricane, the most important factor of disaster relief is the exact location of victims. Once location is communicated, the disaster relief process is able to be more efficient and easier than if disaster location is unknown. As a matter of fact, disaster relief workers are going to find victim(s) directly without additional

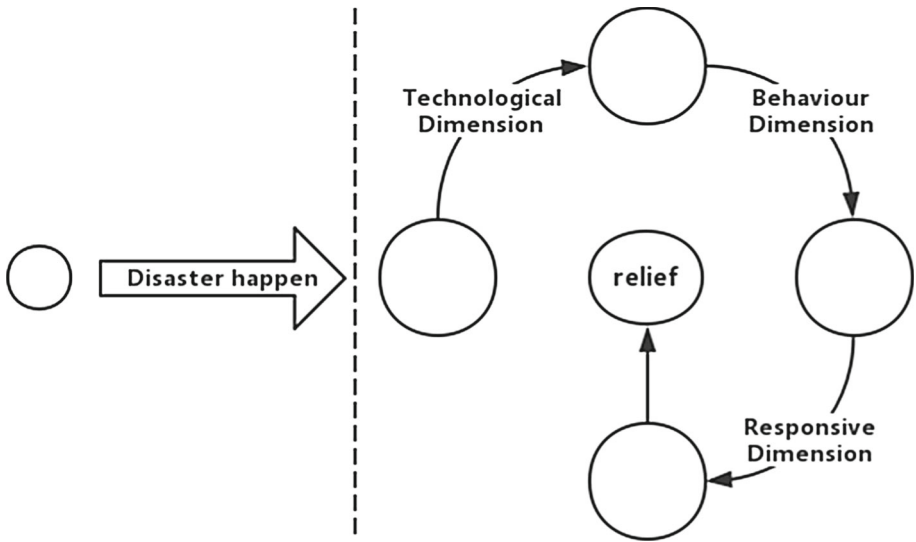


Fig. 1 The relief model

procedures, or they can airdrop relief supplies to the identified location even if workers are not physically present in the disaster region, which is what we want to highlight in this paper.

For social media, some studies have attempted to figure out what technical issues might be challenging when it's exploited. One major common challenge is the processing of collected data produced by social media during disasters (Rogstadius et al. 2013). It is widely believed that precise and timely processing of such data is able to greatly improve the efficiency of relief process. In our study, we mainly focus on the accuracy of the data about victims' location. The more accurate the location is, the better the disaster response will be (Fig. 1).

3.1.2 The IoT devices

As defined earlier in this paper, Internet of Things (IoT) indicates that interconnectivity between various devices, which comes often with RFID technology (Radio Frequency Identification Device). In fact, the interaction between the RFID equipment is an interesting thing, which we think is very helpful in disaster response. In the above part, we throw the idea that once we learn the exact location of victims, the relief process will be expedited. However, the relief workers usually are NOT able to arrive at the location immediately for many reasons such as the roads are destroyed during the disaster or the lack of manpower. Therefore, the fastest thing workers can do is airdropping relief supplies to the specific spots such that victims can find supplies for victims to accomplish self-aid. We can't help but wonder: how can IoT be incorporated into this? It has come to our minds that relief supplies could be connected to each other as a system of IoT. In other words, relief supplies can be equipped with RFID equipment. Once a victim obtains such a relief supply, by using RFID equipment a victim can surely find other relief supplies or other victims with relief supplies. The more relief supplies victims obtain, the more victims gather together, the more likely they will survive the disaster.

From another special perspective, whether a victim trusts the information that RFID equipment offers is a problem needed to be taken into consideration. There are some related

literatures concerning the trust between human-IoT relationships. Kounelis et al. (2014) discussed the trust problem in their paper. They think there are some challenges in building a Human-IoT trust relationship and proposed a model-based framework to build such relationship. Gao and Bai (2014) propose an IoT acceptance model which consists of six factors affecting the consumer acceptance of IoT. What we want emphasize here is that trust is still an important element we cannot neglect when applying IoT technology. Therefore, it is necessary for us to consider this factor in disaster relief. Another factor is that the ease of use of IoT devices. Even though the IoT is quite ubiquitous, we have to admit that there are still a lot of people don't know how to use it, especially in the rural areas where the disaster often causes the most severe consequences. The more people know how to use it, the more people accept it, the better relief process can be. Therefore, the ease to use IoT devices is one topic we should pay attention to and the IoT devices themselves should be better designed. Several studies have examined issues related to the use of crowdsourcing and IoT, such as the use of social networks (Antikainen et al. 2010), collaboration tools (Blohm et al. 2011; Schweitzer et al. 2012) and so on.

The two key technologies, the crowdsourcing based social media and the IoT devices, are the base of our relief model. Their perceived usefulness and ease of use have important influence on our model's application, which means our model could be futile and worthless if the two aspects failed to be recognized.

3.2 Behavioral dimension

In this paper, we want to fully emphasize the role of victims in disaster response. In many cases, victims are put in a very passive environment: they encounter a disaster, they wait for assistance and there are few things they can do about it. On the contrary, we believe that the victims' potential is far underdeveloped. As mentioned before, victims can provide vital information through social media such as their location. Once victims got relief supplies, victims themselves, of course, can conduct self-aid and find other victims. More importantly, victims may use relief supplies to rescue other victims. In general, we hold the standpoint that victims are active rather than passive people waiting for food: victims have the motivation to do what they can to minimize the damage near them. Therefore, victims, as the crowd in our paper, can bring significant meanings to the disaster response.

Moreover, attention should be paid not only to behaviors between human beings, but also behaviors between human beings and machines including trust among the crowd and machine and the interaction of individuals in social media. Although social media can positively impact disaster relief efforts (Gao et al. 2011), in the context of crowdsourcing and IoT usage, many victims, especially those living in rural area where disasters usually cause severe damages, are unfamiliar with these electronic devices. This phenomenon has been regarded as one critical concern in regards to the security of information. Besides, consumers' trust about IoT technologies is believed to play a critical role in consumers' adoption about IoT. This implies that service providers are supposed to be cautious when dealing with this issue, which can be very pivotal (Gao et al. 2014), and some studies have also examined issues related to cheating (Eickhoff et al. 2013; Yuen et al. 2011) and trust (Jain et al. 2010) in crowdsourcing. In disaster relief, the analysis techniques of social media and the usage of IoT equipment are still at the elementary stage of development, which highlights the importance of the interaction behavior, trust behavior and security behavior. Hence, these enablers may be included in the same dimension.

3.3 Responsive dimension

In this dimension, as we said before, victims as the crowd will fully play their roles. They can conduct self-aid, they can help other victims who needed help, and they can do whatever they can to minimize the damages. It's believe that as long as the technological and behavioral dimensions are well accomplished, the relief process will smoothly step into the responsive dimension.

In the above part, we have introduced the three dimensions. Let us sort out the logic from the beginning to the end. The first is technological dimension. The technologies in our model are social media and the IoT, which should be designed to be easier to be used. At the same time, the trust between people and machine should be built. This is the sufficient condition for people to use such technologies. The second is behavioral dimension. The people not only interact with machines but also with the people themselves. People perceive the usefulness and ease of use of the technologies, so the technologies will be better exploited. Meanwhile, people will cooperate with each other and help each other. The third is responsive dimension. The relief process will smoothly step into the responsive dimension as long as the technological and behavioral dimensions are well accomplished, which is the reason that we mainly put our eyes on the technological dimension and behavioral dimension.

4 Simulation experiment

To investigate the impact of crowdsourcing and IoT on disaster response, we conduct a computational experiment based on the SIR model. The simulation software we use is NetLogo. It is a multi-agent programmable modeling environment and it has been successfully applied in many fields like social network, biology and traffic.

4.1 The SIR based simulation

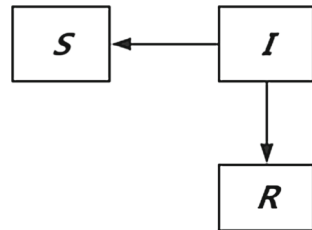
The SIR model, initially developed by Ronald Ross, William Hamer, and others in the early twentieth century (Anderson 1991), was in the beginning used to study the mechanism of epidemic transmission. This model consists of three separate but related parts and each part represents a certain type of people in the process of epidemic transmission. Between 1927 and 1933, Kermack and McKendrick did some theoretical works, which have a great influence in the development of mathematical epidemic models. In fact, epidemic model has provided us with an effective methodology such that we can harness it to study many problems. Many researchers have used this model to explore diseases like Dengue Fever (Rodrigues 2009), SARS (Shi et al. 2004; Mummert et al. 2011). Except this particular field, the epidemic model is increasing applied in fields like online social networks, viral marketing, and informatics and so on. For example, Wang et al. (2013) used an epidemic inspired approach to model the tweets' spread behavior in microblogs and predict future retweeting trends. Rodrigues and Fonseca (2016) held that viral marketing is similar to the spread of infectious disease and proposed a SIR based model to study of the effects of a viral marketing strategy. Bernardes et al. (2012) did some simulations to evaluate the relevance of the SIR model to mimic important elements of spreading cascade in P2P file sharing system.

The epidemic model can be applied in disaster relief because it exists several analogies between disaster and epidemic model, especially the SIR model:

Susceptible (S) is the class of individuals who are in the disaster area. These people can move freely in the disaster area and they can help and rescue other victims;

Table 1 Categorizing three types of people in disaster affected area

SIR model	Susceptible	Infectious	Recovered
Disaster	Free-moving victims	Trapped victims	Dead victims

Fig. 2 Schematic diagram of disaster transmission

Infected (I) in this class, these victims are trapped in a certain spot so that they cannot do anything at all but to wait for rescue. In addition, they have a chance to die and this chance will increase with time going by.

Recovered (R) is referred as dead victims.

What's more, the total number of victims, i.e., $N = S + I + R$, in the disaster area is nearly unchanged, therefore it can be considered as a constant. This setting is also similar to the SIR model.

We can clearly see that the epidemic model has been successfully applied in so many domains so far. Coincidentally, the disaster relief bears some similarity to epidemic transmission, which is why we want to use the SIR model to find out the underlying mechanism. When disaster happens, there are three types of people in the affected area. The first type is these individuals who are in the area, however, they can move around freely in the disaster area, which means that they can help other victims and rescue them. The second type is these individuals who are trapped in some certain spots so that they cannot move freely. All they can do is to wait for other people's rescue. The third type is these individuals who are, unfortunately, dead. These three types of individuals can be considered as the Susceptible, the Infectious, the Recovered respectively. We summarize it in Table 1.

On the other hand, there are some transmission mechanisms between the three types of victims. Firstly, because these S-type victims can move freely in disaster area, this determines that they can rescue these trapped victims. Therefore, the I-type victims will become S-type victims under some conditions. In addition, on account of these I-type victims being trapped in some spots, they might be injured and couldn't access food and water. Thus they may die if they fail to get timely rescue. The longer they wait, the more possibly they die. We illustrate this spread process in Fig. 2. Similar to the SIR model, the total number of victims in disaster area remains a constant, i.e., $N = S + I + R$, N is unchanged.

One element we need to characterize is the use of social media. We have discussed before that if one person uses social media to post some information, we can sometimes obtain his location information. Now let's think this scenario. When disaster happens, there is a person in the disaster area, and he will do whatever he can to live. If he has a phone, there is a great possibility he will ask for help through social media. When we detect such information, we can analyze where he is and airdrop some relief supplies to his location. Once he gets the relief supplies, he can use these supplies to accomplish self-aid and help others. This scenario exists because sometimes when disaster happens, the professional rescuers cannot arrive at

the disaster area in the first place. In this situation, airdropping relief supplies will be the first choice because of its rapidity and convenience. When the relief supplies contain IoT equipments, things might be different. We will talk about this later. Thus the more victims use social media, the more relief supplies will be obtained, the more IoT equipments they will have.

As discussed before, every S victim can help rescue other I victims but the rescue radius is limited. It is worth noting that usually one person cannot rescue a victim on his own, so they need to cooperate with others to do that. Each S victim has a rescue radius and he can help rescue these I victims inside this radius, hence whether an I victim can be rescued depends on how many S victims are near him. In other words, the degrees of I victims determines are the keys in disaster relief. It has come to our attention that the IoT equipments can enlarge the rescue radius. We assume that S victims can get IoT equipments with a certain chance. With IoT equipments, the rescue radius of S victims will be enlarged. Here we define that the rescue radius is l without RFID equipments and L with RFID equipments. Each I victim's degree consists of two parts: the S victims with IoT equipment whose rescue radius is L and the S victims without IoT equipment whose rescue radius is l . We use D_i and d_i to represents the two parts for a given I victim i . Therefore, the degree of I victim i is $d_i + D_i$. We suppose that the threshold of degree is K , i.e., if $d_i + D_i \geq K$, then I victim i will be rescued and become a S victim and we assume he then can help rescue other I victims.

The I victims are trapped in some spots. They might be injured and can't access resources like food and water, so they might die after some time. We assume that the death probability of I victims is P_t at time t . The longer they wait, the more likely they will die, i.e., $P_i \leq P_j$ if $i \leq j$. If an I victim die, he will become a R victim.

The SIR model can be represented as follows:

$$\begin{cases} I_{t+1} - I_t = - \sum_{i=1}^{I_t} x_i^t - P_t I_t \\ S_{t+1} - S_t = \sum_{i=1}^{I_t} x_i^t \\ R_{t+1} - R_t = P_t I_t \end{cases}$$

$$x_i^t = \begin{cases} 1, & \text{if } d_i^t + D_i^t \geq K \\ 0, & \text{if } d_i^t + D_i^t < K \end{cases}$$

4.2 Experiment design

Assuming that after the disaster, the traffic and communications in the disaster area are often destructively damaged, therefore, for buying rescue time and ensuring the post-disaster life safety of the victims, DRWs (disaster relief workers) decide to airdrop relief supplies. Delivering the relief supplies to the victims efficiently and effectively is very necessary for the self-aid and buddy-aid when DRWs fail to arrive at the disaster area promptly. This measure will reduce casualties of the disaster and improve disaster response speed. Additionally, we assume that the victims randomly distributed in the affected areas, some of the victims were trapped in a fixed location and cannot escape by themselves. The victims can find others within a certain distance and carry out self-aid and buddy-aid, and two or more S victims can rescue one I victim. As long as I victims are rescued, he can help to rescue others. We assume that the management of disaster relief team decides to adopt crowdsourcing & IoT for disaster relief. The adjustable variables are: the proportion of social media use, the degree of trust, ease to use of IoT devices. Sensitivity analysis is conducted to analyze how the changes of the adjustable variables would affect the effect of disaster response.

Three groups of simulation experiment were carried out to observe the changes of every type victims. To fully characterize the influences of different variables, we designed a series of three simulation experiments as follows:

- *Control group* DRWs randomly airdrop the relief supplies to the disaster area;
- *Experimental group 1* The IoT equipment (such as high frequency wristbands and reader; GPS devices etc.) is binding in the relief supplies package. The victims can find relief supplies within a certain distance. When the S victims get relief supplies, they can enlarge their rescue radius through the IoT equipment, and find and rescue other I victims and share supplies.
- *Experimental group 2* The mobile devices (i.e. they can still use social media to ask for help) are still available for some victims. They sent the instant messages or contents to the outside world by SMS or twitter and so on. The crowds capture these related information and spread on the internet. Then the DRWs capture these messages from internet and learn about the approximate locations of the victims. According to the location information, DRWs will airdrop part of the relief supplies on the assigned fixed-point, and airdrop other relief supplies randomly. In the meantime, these relief supplies are equipped with IoT devices.

For each group, there are 300 S victims and 200 I victims randomly distributed in a disaster-affected area. In practice we conduct a series of simulations using different numbers of victims. Despite of the different numbers of victims, the trends of results are nearly the same. Only the exact numbers changed.

5 Result analysis

We firstly report the results of the experiments and then conduct a series of sensitive analyses to investigate the role of social media and IoT technology, in the disaster relief.

5.1 Results of experiments

From Fig. 3 we can see that the results of both two experimental groups are better compared to the control group, i.e., the S victims are more. Specifically speaking, with the introduction of Social media and IoT, experimental group 2 has the best results while control group has the worst one. In experimental group1, with the IoT equipments, through such devices S victims can enlarge their rescue radius to rescue I victims. Once the I victims are rescued, they become S victims and they can help other I victims. At the same time, less I victims will die. In experiment group 2, with the use of social media, the DRW can airdrop the relief supplies to victims' location, which means that S victims are more likely to obtain IoT equipments to rescue I victims.

After deriving the above results, we'd like to continue to find out how the changes of adjustable variables affecting the results. Here we use to the final number of S victims to characterize the result.

5.2 Sensitivity analysis

1. The accuracy of processing social media data

Figure 4 shows that with the change from 0 to 1 of the precision of processing social media data, the S victims become more and more. The intuition is that, when more and

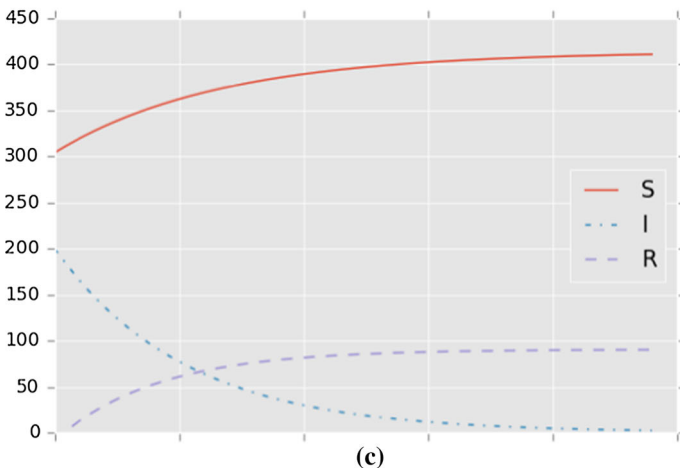
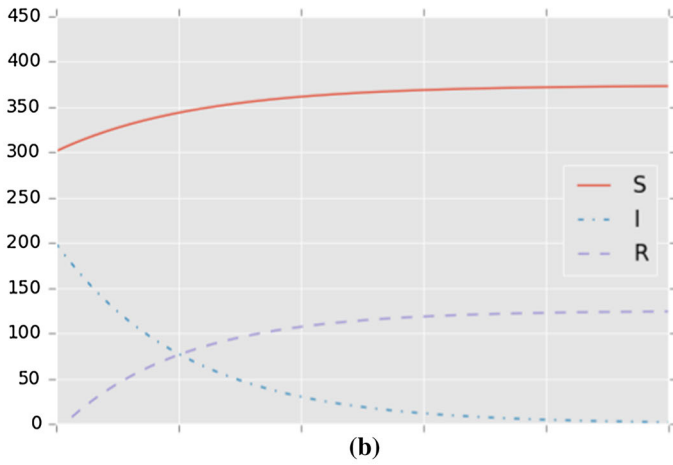
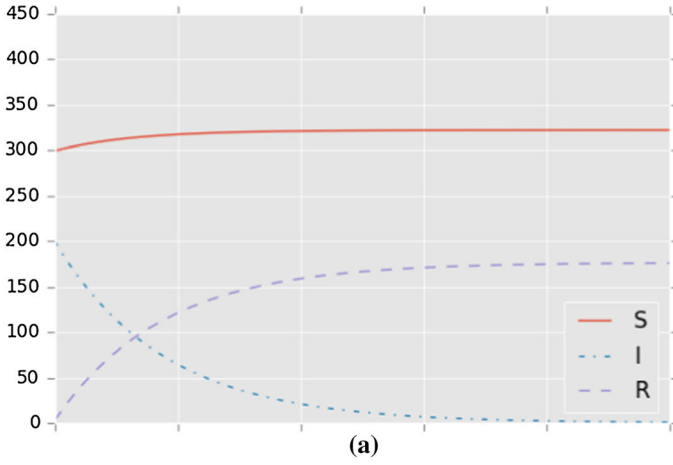


Fig. 3 The results of three experiments. a Control group. b Experimental group 1. c Experimental group 2

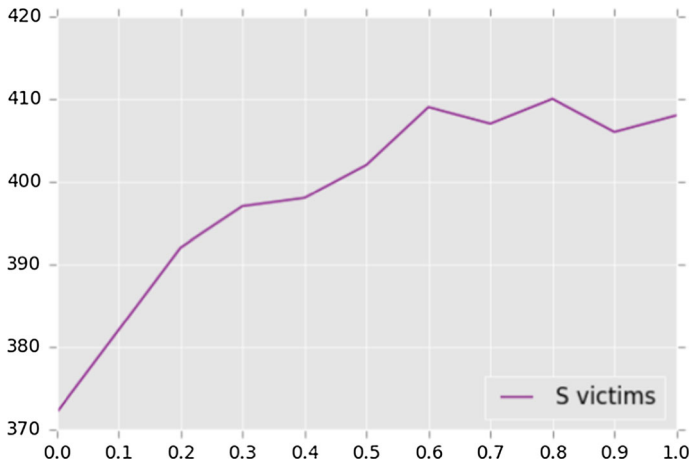


Fig. 4 The effect of the accuracy of processing social media data on changes in number of S victims

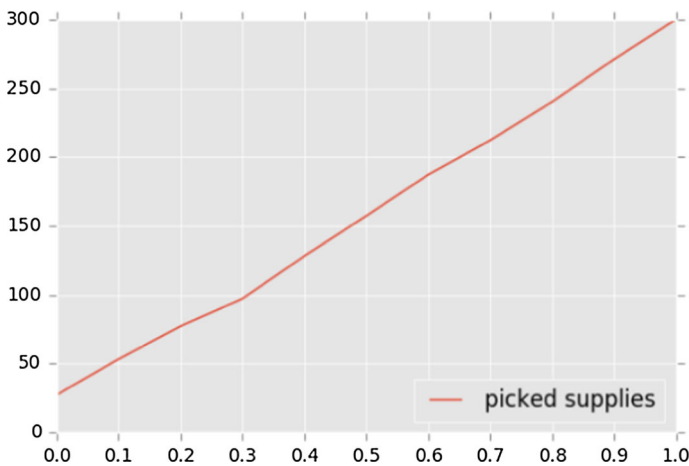


Fig. 5 The effect of the precision of social media on growing picking of relief supplies

more geographical information hidden in the social media data can be precisely learned, more and more relief supplies are airdropped to their locations. Therefore, they can use these supplies to rescue I victims. Another thing we should notice is that, when the accuracy is relatively higher, the S victims see little increment. This may be because that the accuracy is higher enough to cover the whole disaster area. Thus there is no need to require one hundred percent accuracy to achieve better disaster relief. On the other hand, we can easily infer that the relief supplies will be picked more with the use of social media increasing as shown in Fig. 5. So there will be more picked and less wasted supplies. When accuracy becomes 1.0, this means that every S victim has one relief supply and no supplies will be wasted.

2. The Ease to Use of IoT devices

We use the proportion of victims who can use the IoT devices correctly to represent the ease of use of IoT devices. From Fig. 6 we can see how S victims change with device's

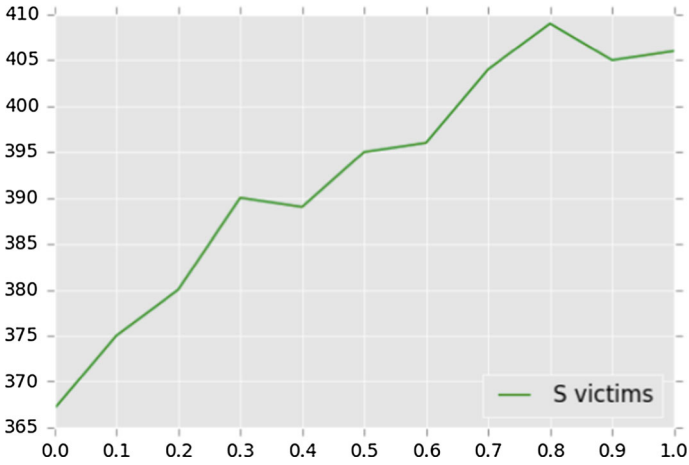


Fig. 6 The effect of ease to use of IOT devices on changes in number of S victims

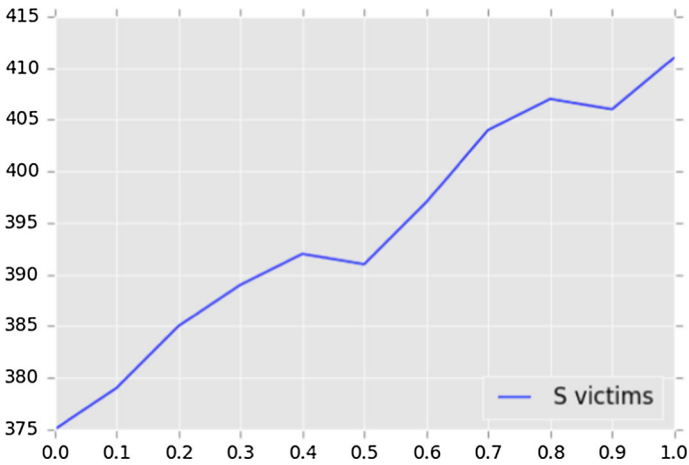


Fig. 7 The effect of trust in IoT on changes in number of S victims

usability varying from 0 to 1.0. With usability increasing, more I victims are successfully rescued and S victims will be more. This means that when usability increases, more victims know how to use such equipments and harness it to rescue other I victims.

3. Trust of IoT

Trust of IoT technologies and service providers is believed to play a pivotal role in adoption intention. As an important variable in IoT adoption, we try to find the impact of trust on disaster response. From Fig. 7 we can see how S victims changes with the trust of IoT varying from 0 to 1.0. The trust of IoT is similar to the usability of IoT equipments. With trust increasing, S victims are more willing use such devices to rescue I victims. Therefore, S victims will be more.

4. The enlarged rescue radius by IoT devices

As we discussed before, when S victims obtain IoT devices, their rescue radius will be enlarged. This has proposed a question: to what extent will the enlarged radius changes

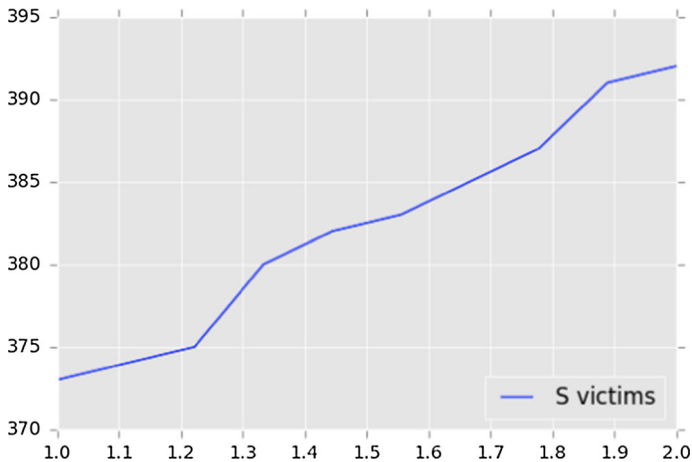


Fig. 8 The effect of enlarged rescue radius on changes in number of S victims

impact the disaster relief? In order to answer this question, we carried out a sensitivity analysis with radius changing from the original radius to twice the original radius. As we can see from Fig. 8, the S victims increase with the rescue radius and this result is as expected.

6 Conclusion

In this paper, we have attempted to develop a crowdsourcing and IoT integration model which can help improving disaster response by using important derived value through using social media and RFID technology, which are two representative features of crowdsourcing and IoT that can make significant differences in disaster response. In addition, we had adopted the extensively used epidemic model to further construct our relief model.

Results suggest that integration of both crowdsourcing and IoT can lead to improvements in disaster response. Our relief model can be very helpful if measures aforementioned can achieve an ideal level such as the trust between human and IoT being developed and more people knowing how to use such devices, which both lead to reduction in behavioral uncertainty. Also, we found that disaster response become more effective with the introduction of social media and IoT equipment. First, the utilization of social media can mainly improve the efficiency of relief supplies airdropping, and the utilization of IoT technology can mainly improve the efficiency of rescue. Second, in our relief model, social media, the ease of use to IoT devices and trust would all increase the number of S victims and reduce R groups. Third, social media has significant impact on obtaining relief supplies, and the ease of use of IoT devices is a crucial factor in the rescue of trapped victims. From now on, the processing of social media data becomes one of the biggest challenges we face due to the current format of social media data (usually text data, and often carry noises). We anticipate that such issues will not stand in the future, due to technology advances.

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