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Using Mobile Phone Data for Emergency Management: a Systematic Literature Review

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Abstract
Emergency management (EM) has always been a concern of people from all walks of life due to the devastating impacts emergencies can have. The global outbreak of COVID-19 in 2020 has pushed EM to the top topic. As mobile phones have become ubiquitous, many scholars have shown interest in using mobile phone data for EM. This paper presents a systematic literature review about the use of mobile phone data for EM that includes 65 related articles written between 2014 and 2019 from six electronic databases. Five themes in using mobile phone data for EM emerged from the reviewed articles, and a systematic framework is proposed to illustrate the current state of the research. This paper also discusses EM under COVID-19 pandemic and five future implications of the proposed framework to guide future work.

Keywords Mobile phone data · Emergency management · Systematic literature review · Systematic framework · COVID-19 pandemic

1 Introduction

Emergency situations such as terrorist attacks or earthquakes occur at different scales daily around the world. They may be natural or human-caused events that occur suddenly, affect public order, and disrupt the regularity of an area's political, economic, and social life (Fogli et al. 2017; Seba et al. 2018). Such an emergency causes great losses and widespread impacts on society, and "requires a prompt intervention by all involved stakeholders" (Fogli et al. 2017; Lauras et al. 2015). To gain public support and maintain regular social order, authorities should pay special attention to the effective management of such situations. In this study, emergency management (EM) is defined as the effective organization, direction, and management of both emergency-related humanitarian and material resources (Othman and Beydoun 2013). Traditionally, it comprises four phases: mitigation, preparedness, response, and recovery (Othman and Beydoun 2013). EM is generally considered to have undergone three stages (Phillips et al. 2011), including passive response (before the 1950s), active preparation and prediction (1960s–1990s), and whole community response based on integrated information systems (after the 2000s). To align with such developments, scholars have swifted their attention from solving a single issue to focusing on efficient intra-organizational collaboration (Janssen et al. 2010).

Lack of collaboration is the chief culprit in major failures in disaster response and takes the form of a lack of available crisis information or poorly managed information flow (Valecha 2019; Beydoun et al. 2018). Information and communication technology (ICT) and information systems (ISs) are considered as crucial means to enhance the collaboration process and information flow management (Sagun et al. 2009; Ipe et al. 2010). However, a lack of informative and appropriate data hinders further development and practical use of emergency management information systems (EMISs) (Ghosh et al. 2018; Roberts 2011). First, data reflecting

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human behaviors on a large scale are required for each phase of EM, since managing affected people is a crucial part of EM. Second, due to the rapid changes of challenges encountered in EM, data collected promptly and timely are required to support various EMISs for corresponding responses. Finally, EMISs require accurate and objective data to reflect emergencies, while traditional emergency-related data heavily rely on surveys. These three requirements create obstacles for the practical use of EMISs in dealing with real-world emergencies.

Many studies have regarded mobile phone data as a potential data source to fulfill these requirements, because these data reflect human behavior richly and ubiquitously. Globally, in 2017, mobile phones attained a registration number of 103.5 per 100 people, as reported by the International Telecommunication Union (ITU) (Sanou 2017). They have been transformed from a simple communication tool to a multifunctional 'mobile-computer' with the rise of apps on mobile platforms. Mobile phone data such as CDRs and app data can be applied to the analysis of human mobility (Stefania et al. 2018; Duan et al. 2017; Gao et al. 2014; Lwin et al. 2018), social networks (Poblet et al. 2018; Trestian et al. 2017; Ghurye et al. 2016; Dobra et al. 2015), mobile phone usage patterns (Jia et al. 2017; Steenbruggen et al. 2016; Gundogdu et al. 2016; Gao et al. 2014), and geographic location (Lwin et al. 2018; Poblet et al. 2018; Dong et al. 2017; Šterk and Praprotnik 2017); these themes are discussed in additional detail in Section 3. The results can further be developed to address various issues encountered during emergencies, such as predicting epidemic transmission (Bengtsson et al. 2015; Panigutti et al. 2017) and developing pre-warning systems (Zhang et al. 2016; Dong et al. 2017).

Although many efforts have been made to investigate the application of mobile phone data in EM, the knowledge and understanding in this field are still fragmented. Therefore, a systematic framework that synthesizes the fragmented knowledge and provides insights into the-state-of-art of using mobile phone data for EM is needed. This study aims to propose such a framework and provide guidance for further research in this field.

This study is related to two streams of literature reviews, which are using ICT in EM and mobile phone data analysis. On the first stream of using ICT in EM (Martinez-Rojas et al. 2018; Tan et al. 2017), Martinez-Rojas et al. (2018) have reviewed 158 related articles from 2009 to 2018 to discuss current opportunities and challenges of using Twitter for EM. Tan et al. (2017) have summarized the involvement of mobile apps in the crisis informatics literature by reviewing 49 related articles. On the second stream of mobile phone data analysis, Blondel et al. (2015) and Naboulsi et al. (2016) have summarized some studies on mobile data analysis, some of which can be applied in EM. These two literature reviews focused on the method of data mining, while the current study focuses on EM. To sum up, there is a lack of a literature review that considers both the characteristics of mobile phones and using such data for EM.

Three research objectives are undertaken to achieve the goal of synthesizing the fragmented knowledge and providing research guidance: (i) extract basic knowledge (e.g. types of mobile phone data, situations) of EM from the selected studies; (ii) break the boundaries of different disciplines and aggregate each analysis perspective; and (iii) study the identified knowledge and integrate it into a single framework that draws a comprehensive map of existing findings under this subject, and provides future implications.

To attain these objectives, this study follows a methodology of systematic literature review (SLR) and synthesized the results of the reviewed studies into a framework, thus allowing a discussion of future implications obtained from the framework. The next section introduces the research method applied in this systematic literature review, which is followed by an illustration of the five major themes in using mobile phone data for EM. Section 4 presents the proposed framework of using mobile phone data for EM based on the five themes. Section 5 discusses current EM under the COVID-19 pandemic. Finally, this paper discusses future implications and provides a conclusion.

2 Systematic Literature Review

Based on the systematic research methodology (Ghobadi 2015) which is considered as *a means of identifying, evaluating and interpreting all available research relevant to a particular research question, or topic area, or phenomenon of interest* (Budgen and Brereton 2006), this study processes three phases of work, including planning, conducting, and reporting. These phases are graphically exhibited along with their specific steps and objectives in Fig. 1. The research questions and relevant studies have been identified in phase 1, and the studies we reviewed in this paper have been selected through a specific research strategy and inclusion/exclusion criteria illustrated in phase 2. As a result, we have selected 65 papers from six document databases for this review. Note that phases 1 and 2 are both explained in Appendix 1, while the results of Phase 3 are detailed in Sections 3 and 4.

3 Five Themes in Using Mobile Phone Data for EM

3.1 Emergency Situations

To identify the trends of research on emergency situations during the selected period, the 65 reviewed articles have been statistically analyzed by their published years and the types of

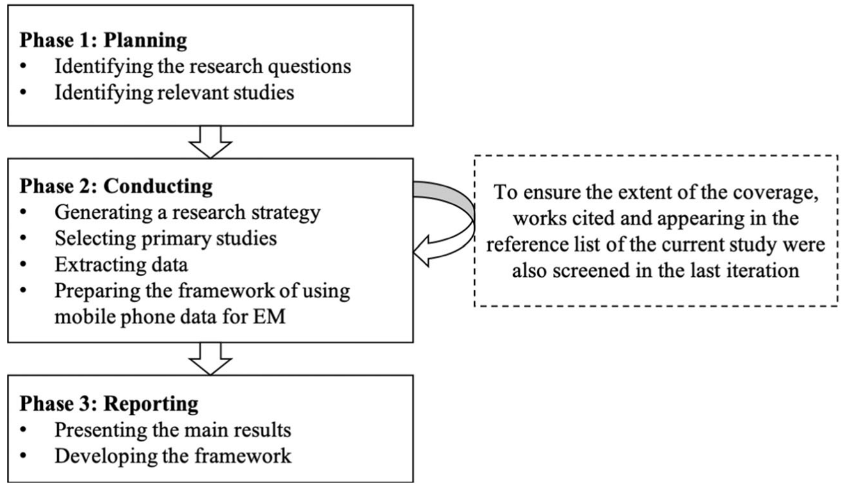


Fig. 1 Three phases of the literature review

situations mentioned in each article. The results are exhibited in Fig. 2.

Emergencies can be divided into two categories, natural (41 papers) and man-made (16 papers). 'Natural' refers to the emergencies that occurred due to processes of the earth (such as weather) that can hardly be avoided, while 'man-made' refers to the emergencies that occurred specifically due to human action or inaction. To be more specific, this paper considers that 'natural' emergencies include 'natural disaster' (19 papers) and 'disease disaster' (22 papers), such as earthquakes and the Ebola virus disease, respectively. Meanwhile, 'man-made' emergencies cover various types, among which 'traffic accident' (six papers), 'violence and terror incident' (six papers), and 'other' (four papers) have been regarded as three major subcategories based on the articles reviewed. The 'others' category includes 'sudden strikes' (Garroppo and Niccolini 2018), 'damages to pipelines' (Dong et al. 2017), and 'refugee problem' (Andris et al. 2019). The remaining studies (eight papers) cannot be clustered into any of the aforementioned categories or subcategories in the course of our review, as they are not clearly related to any particular type of emergency, so we have categorized them as 'general emergency.'

Studies paid considerably more attention to 'natural' emergencies compared with 'man-made' emergencies, and this was particularly evident in terms of disease disasters. We also note that the number of studies peaked in 2015 (13 papers; the other years contained 9, 8, 11, 13, and 11 papers, respectively), and 'disease disaster' has been studied in 2015 (seven papers) almost twice as much as in other years. The phenomenon may have been the result of attention drawn by the outbreak of the Ebola virus.

3.2 Phases of the EM Process

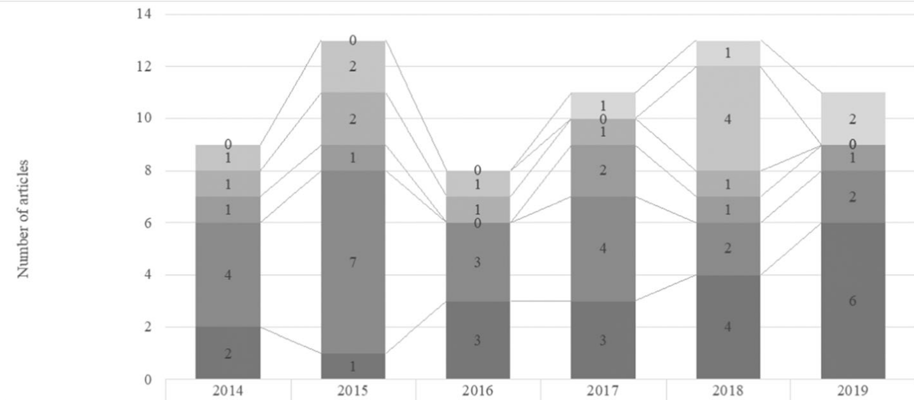
EM generally goes through four phases, namely mitigation, preparedness, response, and recovery. Most of the studies investigated the response phase (39 papers). This phase involves activities like organizing an evacuation, mobilization, and assisting victims to manage the emergency appropriately. Then, 27 papers focused on the preparedness phase, and 22 papers focused on the mitigation phase. The preparedness phase in EM comprises a sequence of activities including planning, training, warning, and updating solutions by learning previous emergencies, which can help enhance response abilities (Oberg et al. 2011). The mitigation phase aims to prevent a disaster or lessen its impacts by modifying the causes and vulnerabilities or distributing the losses (Oberg et al. 2011). Finally, the recovery phase received the least attention from scholars (14 papers). This phase consists of both short-term and long-term activities that are designed for reestablishing and returning disaster areas to normal conditions. Note that the total sum according to these phases (102 papers) is greater than the number of reviewed articles (65 papers) since some studies focused on more than one phase.

3.3 Types of Mobile Phone Data

Mobile phone data consist of information collected by mobile carriers, sensors, and apps on mobile phones. Mobile phone data collected by carriers include CDRs, SMS (short message service) information, traffic volume, etc., and data collected by phone sensors, such as GPS records, Bluetooth-sensed interaction data, etc.

Most of the studies applied CDRs (34 papers) for emergency analysis. This type of mobile phone data contains details about each call such as "the location, call duration, call time, and both parties involved in the conversation" (Trestian et al. 2017). CDRs containing both users' spatial and temporal information can support research on modeling human mobility during emergencies. Moreover, information about caller and recipient IDs reveals individuals' social networks, which correlate to infectious disease dissemination (Gundogdu et al. 2016; Wesolowski et al. 2014).

Fig. 2 Numbers of studies classified by emergency situation and by year



	2014	2015	2016	2017	2018	2019
Others	0	0	0	1	1	2
General emergency	1	2	1	0	4	0
Violence and terror incident	1	2	1	1	1	0
Traffic accident	1	1	0	2	1	1
Disease disaster	4	7	3	4	2	2
Natural disaster	2	1	3	3	4	6

Some studies combined CDRs with other data sources to obtain more comprehensive emergency-related information (Bharti et al. 2015; Pastor-Escuredo et al. 2014). Bharti et al. (2015) used both CDRs and nighttime lighting data from satellite imagery to analyze population sizes and human mobility (the CDRs for short-term and the satellite data for long-term assessment), which helped in making policies and understanding emergency impacts in the response phase. Pastor-Escuredo et al. (2014) adopted both CDR and rainfall-level data in Mexico to help discover anomalous mobile phone usage patterns in seriously affected areas and assess infrastructure damage and casualty populations in time.

SMS (seven papers) is considered as another category of mobile phone data (separate from CDR in this study), which contains both passively collected information like communication details and actively collected information. GPS data (11 papers) can provide the location information of individuals with higher accuracy than CDRs and can be helpful in the identification of individual locations as well as the study of human dynamics. In addition, there were some studies being developed based on app data (six papers) and others (nine papers), such as Bluetooth-sensed interaction data, mobile-phone-usage data, mobile-traffic data, etc.

3.4 Analysis Perspectives

When applying mobile phone data to practical problems, scholars have to gather and extract useful information from the raw mobile phone data. We have categorized different information processing paths from six analysis perspectives: human mobility, geographic location, social networks, mobile phone usage patterns, collected information, and information diffusion (Blondel et al. 2015). Detailed definitions for these analysis perspectives are exhibited in Table 2 (refer to Appendix 2) with specific examples.

As depicted in Fig. 3, spatial-temporal information extracted from CDR and GPS data has been mostly investigated by scholars, which is reflected as human mobility (30 papers). The spatial and temporal information can benefit the tracking of individuals' trajectories and modeling their movement patterns. Since the relationship between human movement patterns and infectious transmission routes were found (Blondel et al. 2015), the analysis of human mobility contributes to the understanding of the disease dissemination process.

Mobile phone usage patterns perspective (10 papers) refers to various individual behavior gathered from one's mobile phone data, such as normal call volume. Arai et al. (2015) found clues to the whereabouts of unobserved populations by analyzing individuals' usage behaviors from CDRs, especially for the whereabouts of children, who are vulnerable to epidemics. This result contributes to tracking epidemic dissemination and the deployment of various resources.

Social networks (10 papers) are constructed based on the communication information gathered from mobile phone data. The analysis of social networks helped to reproduce disease dissemination models and predicted epidemic transmission for the preparedness phase (Y. Chen et al. 2017; Farrahi et al. 2015).

Scholars also used spatial information extracted from mobile phone data (11 papers) at both the individual and aggregate level. The analysis of individual geographic location benefited in tracking anomalous individual locations, and could be further applied to develop pre-warning systems, such as systems to lessen potential damage on natural gas pipelines (Dong et al. 2017).

The collected information (seven papers) perspective refers to the process of gathering multiple types of information content from mobile phones, such as using a specific app to collect public opinions. Deng et al. (2016) collected public

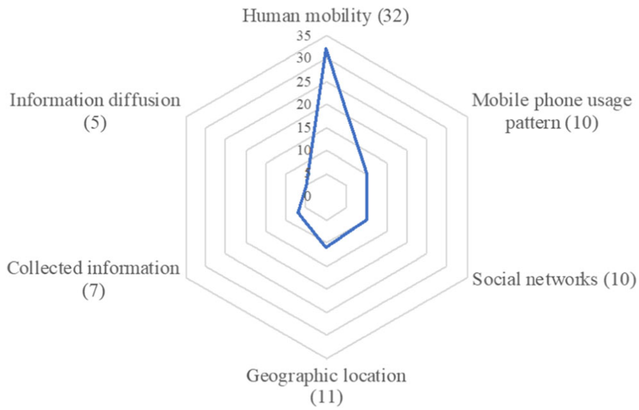


Fig. 3 Breakdown of studies by analysis perspectives

opinions from an online opinion governance app to assist in government decision-making.

In addition, other studies focused on a more general perspective of gathering information from mobile phone data, and this kind of information was defined as information diffusion (five papers). Diffusion strategies of prevention knowledge could be developed to mitigate the impacts of emergencies by analyzing information diffusion networks (Lima et al. 2015).

3.5 Applications

Research in EM mainly focused on five kinds of problems: resource management, evacuation, pre-planning, decision-making, and education and training (Mingliang et al. 2006). Within these five types, various issues (such as making evacuation plans, optimizing resource allocation, predicting epidemic transmission, etc.) are defined as applications in this study.

Although the selected studies developed their unique applications, this study provides a relatively broad classification, five general categories and 13 subcategories to help create a map of the existing applications. This classification is exhibited in Table 3 (refer to Appendix 3) with a detailed definition and a specific example for each category.

Most studies focused on the decision-making problem (42 papers), among which 'conducting public health intervention' (12 papers) and 'processing real-time detection' (12 papers) had been mostly developed. It was followed by presenting emergency impact (seven papers), 'stating policy/regulations' (five papers), 'making construction plans' (four papers), and 'developing emergency-related platforms' (two papers). The decision-making problem aims to give guidance for the relevant work in the EM process.

The pre-planning problem has been studied by 15 papers during these five years, among which eight papers focused on 'predicting epidemic transmission' and seven papers focused on 'developing pre-warning system.' This kind of application aims to anticipate what might happen and to provide an early warning.

Within the evacuation problem (14 papers), 'finding victims' (five papers) and 'making evacuation plans' (nine papers) were studied. It aims to solve the issues of finding and rescuing disaster victims.

Within the education and training problem (seven papers), 'delivering emergency announcement' (five papers) and 'guiding psychological recovery' (two papers) were explored. This kind of problem focuses on spreading emergency-related knowledge for the public and helping the public to face the emergency rationally.

The remaining problem type was the resource management problem (five papers). This kind of problem focuses on the appropriate allocation of both material and human resources according to the distributions of the victims and rescuers.

4 A Framework of Using Mobile Phone Data for EM

Our framework for using mobile phone data for EM is depicted in Fig. 4 and the detailed process is described in Section A.2. The framework synthesizes the five aforementioned themes (i.e., emergency situations, EM phases, types of applications, analysis perspectives, and types of mobile phone data) and illustrates two logical routes with potential correspondences between each theme. The boxes in the framework represent the categories under each theme, and the lines with arrows represent the existing correlation between each theme according to the 65 reviewed studies.

The first type of logical route is the decision-making route (represented as blue lines with arrows in the framework). It starts with the emergency situation theme, goes through the phases of EM, and ends with the application theme. This route assists managers to make emergency-related decisions comprehensively and conveniently during the emergency. They can make specific emergency plans involved in each phase of EM by following the steps: (i) judging what types of emergency the public are encountering; (ii) determining the phases of the emergency in different regions; (iii) figuring out general categories of applications related to the determined phase, and then referring to Table 3 and Fig. 6 (in Appendix 3) for sub-applications ought to be taken; (iv) determining procedure and activities that can be implemented in practice by considering both the characteristics of the encountered emergency and referred applications. For example, during COVID-19, relevant managers can identify the situation as a disease disaster. If the managers judge that the phase of the pandemic is in the 'mitigation,' he/she can take applications in pre-planning, education and training, and decision-making categories into account according to our framework. After referring to Table 3 and Fig. 6, they can consider implementing applications, like

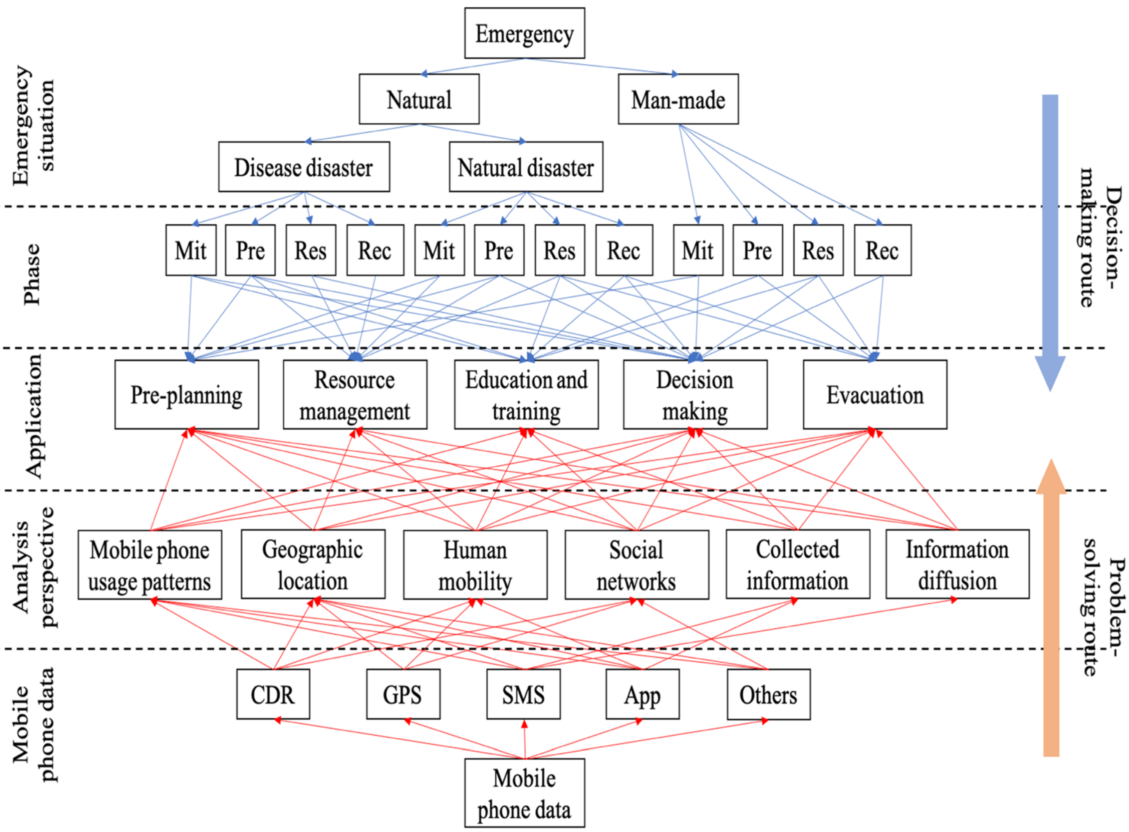


Fig. 4 Framework of using mobile phone data for EM. *Note: Mit = Mitigation; Pre = Preparedness; Res = Response; and Rec = Recovery*

predicting epidemic transmission, as part of their emergency plans to protect communities and reduce loss.

The second type of logical route is the problem-solving route (represented as red lines with arrows in the framework). It ends with the application theme, but starts from the mobile phone data theme while goes through the analysis perspective. This route assists technicians to devise solutions for emergency plans. They can employ mobile technology to implement the identified activities by following the steps: (i) understanding the activity involved in emergency plans given by the decision-maker, i.e. what application is this activity; (ii) identifying appropriate mobile technology that can assist in implementing the application; (iii) gathering information and making appropriate analysis (refer to Table 2) by using the identified mobile technology; (iv) applying the results of analysis into real-world EM. For example, to predict epidemic transmission during COVID-19 pandemic, technicians can find CDR and GPS data appropriate for gathering individuals' spatial-temporal information and analyzing human mobility. They can apply the analysis to technical solutions development and decision-support system.

The framework also contributes to extending and enriching our understanding of the evolving literature of EM. Links in the framework represent existing studies in this field, thereby illuminating the established correlations between the themes and indicating potential research gaps. For example, the studies on education and training applications mainly focus on the disease disaster and man-made disaster, while the focus on natural disasters is limited. Meanwhile, studies only analyze this application from four perspectives while information diffusion and geographic location are missing. Researchers may further consider the feasibility of these two perspectives to analyze this application.

5 EM under the COVID-19 Pandemic

The outbreak of the COVID-19 pandemic in early 2020 has caused huge impacts on global political, economic, and social development (WHO 2020d; W. Chen and Bo 2020). Both emergency-related managers and technicians can refer to the proposed framework for potential decision-making and problem-solving.

Drawing on the decision-making route, emergency managers can determine emergency plans involved in each phase of managing the COVID-19 pandemic. Existing activities under the pandemic fit four categories of applications including predicting epidemic transmission (Jia et al. 2020; Iacus et al. 2020; Gatto et al. 2020), public health intervention (Magklaras and Nikolaia Lopez Bojorquez 2020; Ekong et al. 2020; Canada 2020), delivering emergency announcement (Barugola et al. 2020; Shi and Jiang 2020; Xinhua 2020b), and stating policy/ regulations (Speakman 2020; Hu and Zhu 2020; Canada 2020; Singapore 2020). Specifically, in the mitigation phase, related organizations have predicted epidemic transmission through monitoring population flows to reduce potential risks (Jia et al. 2020; Iacus et al. 2020; Gatto et al. 2020). In the preparedness phase, inspectors and the public have been trained and mobilized to use mobile phone security codes, which help track infection cases and contacts (AGDH 2020; Guinchard 2020; Zastrow 2020). In the response phase, the World Health Organization has announced global objectives including conducting public health intervention by rapidly tracing, finding, and isolating all cases and contacts (WHO 2020b; Cozzens 2020; Magklaras and Nikolaia Lopez Bojorquez 2020). And in the recovery phase, some governments have used mobile technology to aid business resumption with contact tracing applications (Thompson 2020a, 2020b; Sunil 2020; Devonshire-Ellis 2020; Hu and Zhu 2020).

Drawing on the problem-solving route in our framework, relevant technicians can analyze various collected information from mobile devices to implement the aforementioned applications. First, researchers have used CDR data (Jia et al. 2020) and mobile positioning data (Gatto et al. 2020; Iacus et al. 2020) to predict epidemic transmission by capturing and simulating population movements. They have mentioned that their prediction model can conduct risk assessments and plan limited resources allocation as well. Second, contact tracing requires various mobile tools including GPS (Cozzens 2020), Bluetooth (WHO 2020c; Xinhua 2020a), apps (Zhang et al. 2020; Singapore 2020; AGDH 2020), and SMS technology (WHO 2020c) to gather individuals' geographic and health-related information. The analysis of this information can be further applied to conduct public health intervention such as isolation strategies and travel restrictions. Finally, as for business resumption, history trajectories and health status of individuals collected through specific mobile phone apps (Zastrow 2020), SMS (WHO 2020a; McCabe 2020) and GPS technology (Elliott 2020) helps to evaluate their infection risk, which can be used by governments to resume business and study.

Our framework not only covers applications that have already been adopted in this EM, but also provides a reference for future EM. For example, it is possible to consider other applications in our framework such as guiding psychology recovery in the context of COVID-19. The use of hedonic apps after an earthquake has been identified to reduce perceived risk effectively (Jia et al. 2017). Therefore, decision-makers can learn from this knowledge and implement appropriate applications in the recovery phase of managing this pandemic.

6 Future Implications

Future research directions can be implied based on the proposed framework from five perspectives: (1) a focus on man-made emergencies, (2) a focus on the recovery phase, (3) exploring new applications, (4) creating better comprehension of the analysis perspective, and (5) combining other data with mobile phone data.

6.1 A Focus on Man-Made Emergencies

It is reasonable to put forward further research on man-made emergencies with mobile phone data. The results shown in Section 3.1 indicate a greater emphasis on natural emergencies (41 articles reviewed in total) and less emphasis on man-made emergencies (16 articles reviewed in total). However, managing violence and terror incidents is also very vital, because these emergencies happen frequently around the world. For such a crisis situation, it is challenging to gather their information due to the dark side and dynamic nature (Roberts 2011; Skillicorn 2011; Chen et al. 2011).

In view of these challenges, current literature has explored the suitability of using social media data (Oh et al. 2011; Cheong and Lee 2011; Prentice et al. 2011; Qin et al. 2011). However, lacking individuals' real-time location and objective behavior information makes social media data limited. Some studies have identified the feasibility of using mobile phone data in man-made emergencies, such as detecting terrorism attacks and monitoring traffic conditions (Blondel et al. 2015). However, the application of mobile phone data in this domain still has great potential.

6.2 A Focus on the Recovery Phase

A focus on the recovery phase would also be a future direction. The occurrence of emergencies will have both physical and psychological impacts on the victims. However, most scholars focused on the timely and effective response to emergencies, while fewer studies focused on the psychological recovery of people after emergencies. With the popularity and development of 4G/5G communication technology, many people use their mobile phones for obtaining emergency-related information and entertainment to ease their anxiety. For example, Jia et al. (2017) discovered that the use of hedonic apps after an earthquake can help people reduce their perceived risk. Therefore, there is the potential to use mobile phone data for the study of developing positive psychological structures in the recovery phase.

6.3 Exploring New Applications

Additional applications can be explored and expanded according to the two ways demonstrated in the framework. With a further understanding of analysis perspectives (which are discussed in Section 6.4), scholars can explore additional applications. For example, with a more comprehensive notion of human social interaction, scholars may not only investigate approaches in predicting epidemic transmission, but also apply this knowledge to develop systems in predicting crimes. In addition, with the upgrading of mobile phones and ICT (Bandyopadhyay et al. 2018; Palshikar et al. 2018), new applications can be explored under the proposed framework. As a result, additional applications can be similarly explored within and beyond the existing applications in the future.

6.4 Creating Better Comprehension of the Analysis Perspective

Future work should also make efforts to complement the theoretical foundation of emergency studies with theories from other fields. Current literature has developed theories about information transmitted among various stakeholders (Wang et al. 2018; Weidinger et al. 2018; Liu and Xu 2018; Abedin and Babar 2018; Fedorowicz and Gogan 2010), and theories of coordination and political science (Maldonado et al. 2010). Moreover, a better comprehension of the analysis perspective can be made by learning constructs about human behavior, social networks, etc. For example, scholars have found similarities between human communication and infectious disease dissemination (Blondel et al. 2015), which indicates the benefits of drawing on theories from social networks to apply to EM. Meanwhile, the current understanding of human mobility is mainly based on data analysis. If scholars can learn and apply aspects from relevant psychological and behavioral theories, the analysis of human mobility can be further deepened.

In addition, with a better comprehension of analysis perspectives and applications, it is possible to develop new correspondences between analysis perspectives and applications. The current framework was developed based on the 65 articles reviewed, and cannot reveal every possible relationship between analysis perspectives and applications. For example, human mobility can probably be analyzed in order to construct pre-warning systems. According to the study of daily movement patterns of individuals, a detected anomaly of movement may indicate a coming disaster, which would suggest the need to construct correlations between human mobility and pre-warning systems. Consequently, the correspondence between analysis perspectives and applications should be considered and expanded upon in future research.

6.5 Combining Other Data with Mobile Phone Data

Although mobile phone data have been successfully applied to EM, combining other micro and macro data can help the development of EM research more efficiently (Ghosh et al. 2018). Martinez-Rojas et al. (2018) have reviewed 158 articles about using Twitter to manage emergencies, indicating the significant roles and value of data from social media in EM. Under what circumstances it is appropriate and how to combine mobile phone data with micro (e.g., individual locations) and macro (e.g., public opinions) data from social media requires further exploration. Moreover, combining data from other platforms is worth consideration as well. For instance, Pastor-Escuredo et al. (2014) believe there is potential in combining information from officially monitored sensors like traffic video cameras, which can provide a fine-grained validation for the existing measures.

7 Conclusions

Emergencies have great impacts on the whole of society, affecting material facilities and social order in terms of economic losses and human casualties. Unlike traditional management measures based on data sources with limited adaptability and low accuracy, applications for handling emergencies that utilize ubiquitous and real-time mobile phone data have greatly improved EM mechanisms and minimized their negative impacts on society. This systematic literature review analyzes 65 studies concerning the use of mobile phone data for EM, and proposes a framework to synthesize the fragmented knowledge of existing studies. The framework comprises five themes, among which six analysis perspectives and five general types of applications are put forward to explain the EM process, which includes two logical routes. The framework can support stakeholders, such as emergency managers and technicians, and is used to suggest five future research directions in the field for scholars. In addition, this study discusses EM under the COVID-19 pandemic and provides a reference for future management of the pandemic.

Despite all the contributions mentioned above, this study still possesses some inevitable limitations. First, the common limitation of literature reviews related to keywords exists in this study as well. Making the best efforts to alleviate this drawback, this study draws on keywords about EM from previous reviews and research works in the field of EM as well as keywords about mobile phone data. The second limitation is that the framework develops in this study is only based on the articles reviewed, meaning that relationships not mentioned in the articles are not considered. Although this review is intended to be both wide and deep in coverage, it should not be considered as a complete or final summary of the topic. Reviews, no matter how current, by definition focus on the past and cannot fully anticipate novel approaches or new developments. Finally, this study does not focus on the detailed introduction of data processing and analyzing techniques. Nevertheless, we still believe this study makes a strong contribution to the field, especially toward emergency managers and scholars who are looking for direction to develop this field in the future.

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Authors' Contributions YW, JL, XZ, GF, XL conceived the study. YW, JL carried out the review, synthesized and analyzed the evidence, and drafted the manuscript. XZ, XL, GF supervised the review process and revised the manuscript. All authors read and approved the final manuscript.

Appendix 1. Systematic Literature Review

Planning

Identifying the research questions. Our research questions were as follows: (1) What types of mobile phone data—with respect to its applied phases and use to cope with practical issues—have been studied? (2) What is the state of the art of this field? and (3) What can future works develop to facilitate the understanding of this subject?

Regarding the first question, a statistical analysis was performed on the aspects of emergency situations, phases of EM, types of mobile phone data, analysis perspectives, and applications. Next, a framework of using mobile phone data for EM to address the second question was proposed. Finally, five future implications based on the proposed framework are presented in order to address the third question.

Identifying relevant studies. The second step of planning the research was identifying relevant studies, which defines the scope of this review study. Six document databases were searched to find related studies between 2014 and 2019. These were: ScienceDirect, Scopus, Web of Science, IEEE Xplore, ACM, and Springer. IEEE Xplore and ACM are two specialty article databases that provide extensive coverage of the literature in computer science and related areas, and Scopus (SciVerse Scopus) is the largest abstract and citation database. The other three were additional comprehensive and widely searched databases.

To draw the boundaries of what articles would be included and reviewed in the study, the *phenomenon of interest* was identified as 'research that applies mobile phone data to manage emergencies.' We developed an initial list of research keywords to match the definition with published documents and considered various literature expressions that represented the same terminology by considering both aspects of emergencies and mobile phone data. This method is illustrated at the beginning of the conducting phase and further guided the search for related articles.

Conducting

*Generating a research strategy***.** The first step was to generate a research strategy by finding and filtering studies from the six databases. Two iterations were processed: (1) searching 26 terms in the keywords list ("mobile phone data" OR "short message service" OR "call detail record" OR "phone GPS data" OR "cellular network data" OR "app data" OR "application data" OR "Bluetooth data") AND ("emergency" OR "extreme situation" OR "extreme event" OR "large-scale event" OR "special event" OR "special situation" OR "anomalous event" OR "anomalous situation" OR "unusual event" OR "unusual situation" OR "crisis" OR"disaster" OR "catastrophe" OR "traffic accident" OR "epidemics" OR "infectious disease") AND (2013 < PUBYEAR<2019); (2) searching papers in the reference list of the five previously identified review articles and including additional studies.

In the first iteration, 4784 papers (1880 ScienceDirect +1542 Springer +101 IEEE +715 ACM + 276 Web of Science +170 Scopus) were initially identified. In the second iteration, 13 additional articles were included as relevant for further selection by searching the reference lists. Accordingly, 4797 articles were found through the process of this stage (Fig. 5).

Selecting primary studies. The second step was to select the studies to be reviewed through a standard inclusion and exclusion criteria. The specific items are depicted in Table 1. The inclusion criteria I1 and I2 ensured that the selected studies were in accord with mobile phone data and applying it in EM, which aligned with the objectives of this study. The exclusion criterion E1 eliminated studies that were found by the keyword "emergency," but discussed emergency-related activities instead of an emergency situation itself or did not discuss a specific situation at all, for example, studies of efficient deployment of emergency departments or the contents and answers of emergency calls. E2 excluded studies that analyzed the use of mobile phones for self-rescue when individuals encountered difficulties, like heart attacks. Such situations were considered to be emergencies for a single person, which did not fall within the scope of this study. E3 excluded studies with a discussion of non-emergency situations, which were planned events like concerts, festivals, and football matches. All of these criteria were considered to point out the most relevant studies for the topic and improved the reliability and validity of the review study. Finally, in order to mitigate bias, two of the authors conducted this step using the above criteria. After discussion, 65 articles were chosen for the analysis and report in this review (refer to the process illustrated in Fig. 5).

Extracting data. The third step was to extract data from the studies that were selected. The following information was extracted from the 65 studies: (i) document demographic

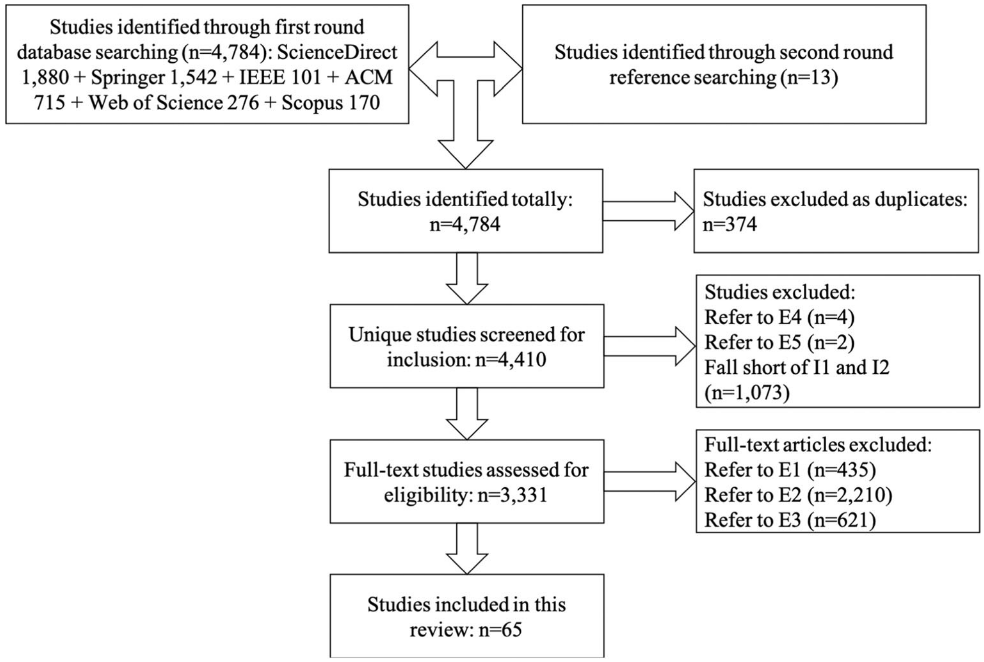

Fig. 5 Study selection process

information, including the title, year of publication, journal name or conference name, and authors; (ii) information about emergency situations, including the general types of emergency and specific events; (iii) types of mobile phone data used in emergency situations; (iv) methods to apply such data in the situations and objectives of the study (what perspectives it analyzed and to which process of EM the study belongs). The detailed results are presented in Section 3.

Based on the information extracted, the analysis perspectives and applications that were proposed were summarized to create a clearer idea of how to apply mobile phone data to effective management (refer to SectionS 3.4 and 3.5 for details). For example, individual movement patterns were studied by Stefania et al. (2018) and Vogel et al. (2015) to either establish new models or develop existing models, and thus help prevent disease dissemination, while aggregated population mobility was analyzed by Sekimoto et al. (2016) to benefit government policymaking. In this study, the phrases 'individual movement patterns' and 'aggregated population mobility' were combined and expressed as 'human mobility,' which represents a kind of analytic perspective. In addition, objectives (or final applications) of the reviewed articles like 'making rescue plans,' 'making traffic regulations,' and 'helping in policy decisions' were paraphrased as 'making policies'. In this way, the current study transferred the meta-information extracted from the reviewed studies into a collective and scientific form for the conclusions and future discussion.

Preparing the framework for using mobile phone data for emergency management. The final step in the conducting phase was to propose the plan for developing a framework that could illustrate the current state of research. First, we drew on the *typology of mobile data sources, types, and uses in the disease disaster management cycle* proposed by Cinnamon et al. (2016), and we planned to adjust the framework to adapt to the data from this study. Second, we considered "emergency situations" and "mobile phone data" as two starting points, as both aspects were key features of the subject. Third, considering the practicality of this framework, it was desired to expand the framework to the perspectives of stakeholders

Table 1 Inclusion/Exclusion criteria

	Inclusion Criteria	Exclusion Criteria
1	**I1**. Articles which clearly describe the applied emergency situations and methods	**E1**. Articles which focus on emergency items (e.g. emergency call or emergency department) other than emergency situations
2	**I2**. Articles which contain the description of mobile phone data types with respect to emergencies.	**E2**. Articles which depict emergencies encountered by a single person instead of society (e.g., a heart attack)
3		**E3**. Articles which describe non-emergency situations (e.g., festivals or concerts)
4		**E4**. Articles for which full text cannot be found
5		**E5**. Articles which are not written in English

from both managerial and technical layers, respectively. Therefore, five themes (situations, phases in EM, mobile phone data, analysis perspectives, and applications) were identified as components in the framework. Based on these themes, we realized that "applications" served as the final consideration regardless of the perspective. Finally, we developed a draft of the framework which started from "emergency situations" and "mobile phone data" and ended in "applications." It consisted of two logical routes: the decision-making, or managerial, route ("emergency situation", "phases in emergency management", and "applications"); and the problem-solving, or technical, route ("mobile phone data", "analysis perspective", and "applications").

Appendix 2. Illustration of Analysis Perspectives

Table 2 Illustration of analysis perspectives

Analysis perspective	Studies	Example article
The *human mobility* perspective refers to capturing citizens' spatial-temporal change patterns, like travel, commuting, migration, etc., from real-time mobile phone data.	Stefania et al. (2018); K. K. Lwin et al. (2018); Garroppo and Niccolini (2018); Duan et al. (2017); Trestian et al. (2017); Ghurye et al. (2016); Sekimoto et al. (2016); Yasumiishi et al. (2015); Bharti et al. (2015); Dobra et al. (2015); Wesolowski et al. (2014); Tatem et al. (2014); Peak et al. (2018); Wesolowski et al. (2017); Panigutti et al. (2017); Flahault et al. (2017); Cecaj and Mamei (2017); Gundogdu et al. (2016); Tompkins and McCreesh (2016); Matamalas et al. (2016); Vogel et al. (2015); Wesolowski et al. (2015a); Wesolowski et al. (2015b); Lima et al. (2015); Tizzoni et al. (2014); Andrade et al. (2018); Takahiro Yabe et al. (2018); Kubicek et al. (2019); Takahiro Yabe et al. (2019a); Takahiro Yabe et al. (2019b) (Total number 30)	This article reproduced individuals' trajectories from CDRs by assessing the possibility of moving between antenna locations in order to prepare some measures to control epidemics (Stefania et al. 2018).
The *mobile phone usage pattern* perspective refers to gathering multiple aspects of the users' normal habits in using a mobile phone, such as the normal call volume and app usage behavior.	Jia et al. (2017); Steenbruggen et al. (2016); Gundogdu et al. (2016); Gao et al. (2014); Pastor-Escuredo et al. (2014); Gariazzo et al. (2018); Reznik et al. (2015); Horsman and Conniss (2015); Arai et al. (2015); Muehlegger and Shoag (2014) (Total number 10)	This article mined the citizens' usage changes in different types of apps before and after a disaster from app usage records to reflect the disaster's impact (Jia et al. 2017).
The *social networks* perspective refers to extracting people's contact network and characteristics from communication behavior, such as calling, sending SMSs, interacting through Bluetooth, etc.	Poblet et al. (2018); Trestian et al. (2017); Ghurye et al. (2016); Dobra et al. (2015); Gao et al. (2014); Baytiyeh (2018); Chen et al. (2017); Farrahi et al. (2015); Lima et al. (2015); Andris et al. (2019) (Total number 10)	This article utilized mobile-phone Bluetooth-sensed data to reflect human interactions and compared them to actual infection cases to simulate the spread of seasonal influenza (Farrahi et al. 2015).
The *geographic location* perspective refers to gathering personal space information from CDRs and GPS data to illustrate geographic networks at both an individual and aggregate level.	K. K. Lwin et al. (2018); Poblet et al. (2018); Dong et al. (2017); Šterk and Praprotnik (2017); Oxendine and Waters (2014); Takahiro Yabe et al. (2018); Marzuoli and Liu (2018); Jacobs et al. (2019); Yin et al. (2019); Andris et al. (2019); Dar et al. (2019) (Total number 11)	This article used mobile-phone GPS-location data to find abnormalities close to a pipeline as a way to detect damaging activities (Dong et al. 2017).

Table 2 (continued)

Analysis perspective	Studies	Example article
The *collected information* perspective refers to gathering multiple types of information content from mobile phones, such as comments and views collected through SMS and apps.	Deng et al. (2016); Al-dalahmeh et al. (2018); Babu et al. (2019); Jacobs et al. (2019); Tao et al. (2019); Kumoji and Khan Sohail (2019); Enenkel et al. (2019) (Total number seven)	This article introduced an app that collected online opinions about emergency management and applied this data into assisting the decision-making of governments (Deng et al. 2016).
The *information diffusion* perspective refers to the network of information propagation via the phone, SMS, or app, which is a general process of gathering information from mobile phone data.	N. Zhang et al. (2016); De Visser et al. (2015); Nan Zhang et al. (2014); M. O. Lwin et al. (2014); Hassan et al. (2019) (Total number five)	This article analyzed the information dissemination mechanisms of calls and SMS messages to validate their effectiveness as pre-warning approaches in reducing losses during emergencies (Nan Zhang et al. 2014).

Appendix 3. Illustration of Applications

Table 3 Illustration of applications

Problems	Specific applications	Studies	Sample quote
Decision-making (Total number 42)	***Processing real-time detectio**n* refers to capturing citizens' anomalous behavior to detect possible emergencies in real-time with appropriate accuracy for planning response efforts.	K. K. Lwin et al. (2018); Garroppo and Niccolini (2018); Trestian et al. (2017); Steenbruggen et al. (2016); Gundogdu et al. (2016); Dobra et al. (2015); Baytiyeh (2018); Cecaj and Mamei (2017); Takahiro Yabe et al. (2018); Kumoji and Khan Sohail (2019); Dar et al. (2019); Enenkel et al. (2019) (Total number 12)	An anomaly detection system was developed by connecting exceptional spatial-temporal patterns from mobile data with real-world emergencies (Trestian et al. 2017).
	Developing emergency-related platforms refers to implementing a better platform to collect multi-source data which eventually enhances the efficiency of EM.	Poblet et al. (2018); Babu et al. (2019) (Total number two)	This study introduced a platform containing multiple kinds of mobile phone data to implement various intervention measures into the whole management process (Poblet et al. 2018).
	Making construction plans refers to scientifically building infrastructure to minimize the loss in an emergency or optimizing reconstruction projects.	Duan et al. (2017); T. Yabe et al. (2017); Andrade et al. (2018); Jacobs et al. (2019) (Total number four)	This study focused on building transportation systems with more adaptability based on an analysis of commuting changes during emergencies (T. Yabe et al. 2017).
	***Conducting public health interventio**n* refers to taking various measures to control epidemics including isolation strategies, population density containment, travel restrictions, border management, etc.	Stefania et al. (2018); Wesolowski et al. (2014); Tatem et al. (2014); Wesolowski et al. (2017); Flahault et al. (2017); Finger et al. (2016); Matamalas et al. (2016); Wesolowski et al. (2015a); Lima et al. (2015); Arai et al. (2015); M. O. Lwin et al. (2014); Kumoji and Khan Sohail (2019) (Total number 12)	Two isolation strategies for controlling epidemics, at the subprefecture and individual level, were proposed based on a model of citizens' trajectories (Stefania et al. 2018).
	Stating policy/regulations refers to related governments drawing experience from current and previous emergencies and utilizing regularities to manage emergencies.	Deng et al. (2016); Gariazzo et al. (2018); Peak et al. (2018); Horsman and Conniss (2015); Muehlegger and Shoag (2014) (Total number five)	This study validated the correlation between the call volume and the likelihood of nearby traffic accidents to illustrate the necessity of a 'No Calling while Driving' regulation (Muehlegger and Shoag 2014).

Table 3 (continued)

Problems	Specific applications	Studies	Sample quote
	Presenting emergency impacts refers to utilizing mobile phone data to reveal crisis influence on infrastructure or human behavior for responsible authorities.	Jia et al. (2017); Bharti et al. (2015); Gao et al. (2014); Pastor-Escuredo et al. (2014); Babu et al. (2019); Jacobs et al. (2019); Enenkel et al. (2019) (Total number seven)	This study represented the population size changes after a political conflict as supporting information provided for governments (Bharti et al. 2015).
Pre-planning (Total number 15)	***Developing pre-warning system*** refers to integrating multiple characteristics concerning diverse emergencies obtained from the analysis stage to give early warning.	N. Zhang et al. (2016); Dong et al. (2017); Steenbruggen et al. (2016); Nan Zhang et al. (2014); Babu et al. (2019); Hassan et al. (2019); Tao et al. (2019) (Total number seven)	An early warning system for motorway traffic was built based on the phenomenon that mobile phone usage patterns are strongly affected by traffic incidents (Steenbruggen et al. 2016).
	Predicting epidemic transmission refers to modeling the propagation of infectious diseases through human mobility or interaction to mitigate and prepare for them in advance.	Bengtsson et al. (2015); Panigutti et al. (2017); Chen et al. (2017); Tompkins and McCreesh (2016); Vogel et al. (2015); Farrahi et al. (2015); Wesolowski et al. (2015b); Tizzoni et al. (2014) (Total number eight)	This study validated that a mobile phone dataset performed better than traditional survey data in representing commuting patterns to simulate an epidemic spread (Panigutti et al. 2017).
Evacuation (Total number 14)	***Finding victims*** refers to providing information or clues about victims' whereabouts for responsible authorities.	Yasumiishi et al. (2015); Al-dalahmeh et al. (2018); Baytiyeh (2018); Reznik et al. (2015); Andris et al. (2019) (Total number five)	This study utilized previous mobile phone usage patterns to predict victims' possible positions when telecommunication facilities were damaged in a disaster (Yasumiishi et al. 2015).
	Making evacuation plans refers to applying individuals' location information as well as crisis information into planning appropriate evacuation routes.	N. Zhang et al. (2016); Duan et al. (2017); Sekimoto et al. (2016); Šterk and Praprotnik (2017); Oxendine and Waters (2014); Takahiro Yabe et al. (2019a); Yin et al. (2019); Takahiro Yabe et al. (2019b) (Total number nine)	This study analyzed citizens' evacuation routes after a subway accident to optimize future evacuation organizing work (Duan et al. 2017).
Education and training (Total number seven)	***Guiding psychological recovery*** refers to discovering people's anomalous behaviors after emergencies to specifically provide psychological counseling for them	Jia et al. (2017); Baytiyeh (2018) (Total number two)	This study found that hedonic behavior would reduce perceived risks by studying app usage changes in a disaster and recommend hedonic app using for the public after disasters (Jia et al. 2017).
	Delivering emergency announcement refers to propagating knowledge or messages about emergencies to help citizens prepare for or respond to them.	Al-dalahmeh et al. (2018); Matamalas et al. (2016); Lima et al. (2015); Hassan et al. (2019); Dar et al. (2019) (Total number five)	By analyzing the social communication via mobile phones during disease disasters, this study introduced information spreading about preventive and curative measures through the social network to control diseases (Lima et al. 2015).
Resource management (Total number five)	***Optimizing resource allocation*** refers to allocating resources such as food and medicines appropriately according to the distribution of victims to satisfy public needs as well as address possible shortfalls.	De Visser et al. (2015); Ghurye et al. (2016); Flahault et al. (2017); Matamalas et al. (2016); Marzuoli and Liu (2018) (Total number five)	This study improved the inference of the hotspot of epidemics based on human mobility mining to optimize resource deployment (Matamalas et al. 2016).

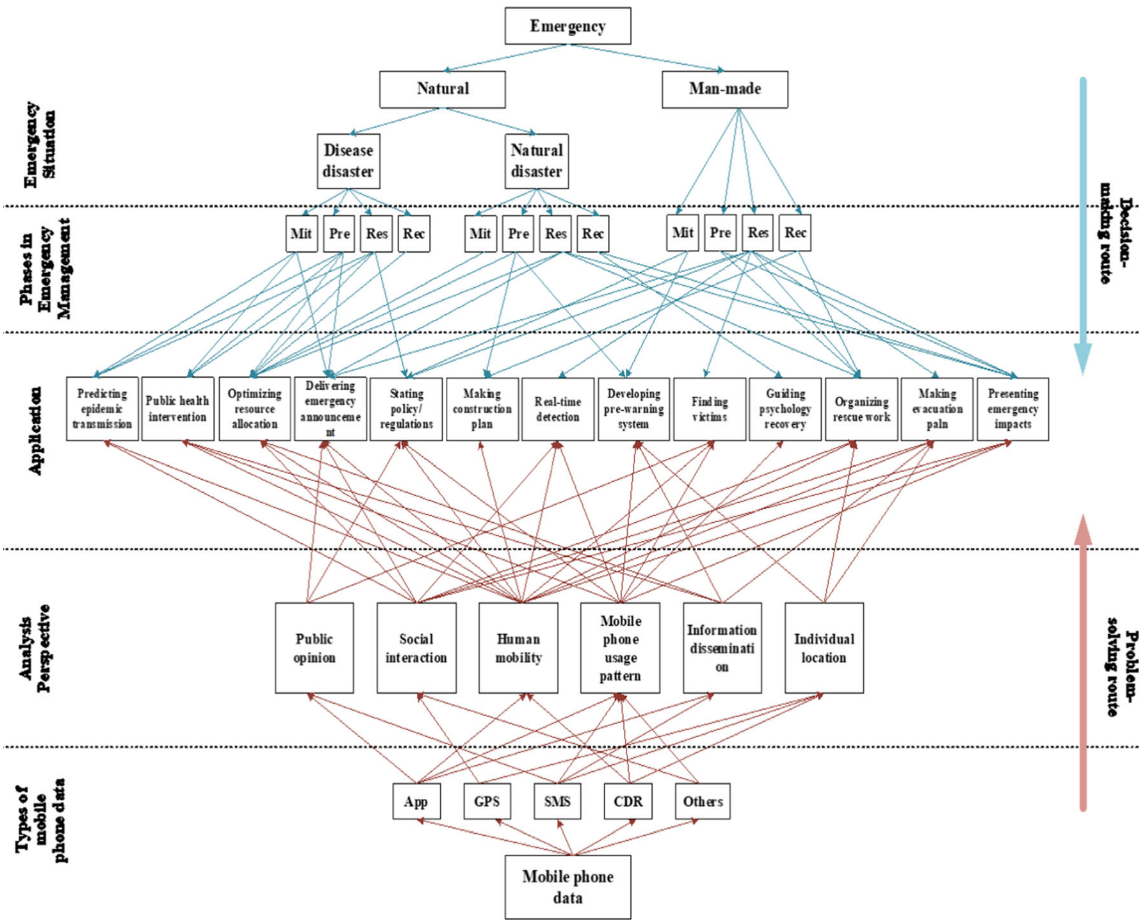

Fig. 6 Framework of using mobile phone data for EM (with sub-applications)

Appendix 4. Characteristic matrix of the reviewed studies

Table 4 Characteristic matrix (data types, analysis perspectives, applications, EM phases)

No.	Research publications	Types of mobile phone data					AP	Applications	EM phases			
		CDR	GPS	SMS	APP	Others			Mit	Pre	Res	Rec
1	Stefania et al. (2018)	♦					HM	conducting public health intervention	♦			
2	Garroppo and Niccolini (2018)	♦					HM	processing real-time detection			♦	
3	Lwin et al. (2018)	♦					HM, GL	processing real-time detection		♦	♦	
4	Al-dalahmeh et al. (2018)			♦			CI	finding victims, delivering emergency announcement			♦	
5	Deng et al. (2016)				♦		CI	stating policy/regulations			♦	
6	Baytiyeh (2018)					♦	SN	finding victims, processing real-time detection, guiding psychological recovery			♦	♦
7	Gariazzo et al. (2018)					♦	MPUP	stating policy/regulations	♦	♦		
8	Peak et al. (2018)	♦					HM	stating policy/regulations			♦	
9	Poblet et al. (2018)		♦		♦		SN, GL	developing emergency-related platform	♦	♦	♦	♦
10	Dong et al. (2017)		♦				GL	developing pre-warning system	♦			
11	Duan et al. (2017)	♦					HM	making construction plan, making evacuation plan			♦	♦
12	Trestian et al. (2017)	♦					HM, SN	processing real-time detection			♦	
13	Jia et al. (2017)				♦		MPUP	presenting emergency impactsguiding psychological recovery				♦
14	Yabe et al. (2017)	♦			♦		HM	making construction plan		♦		
15	Wesolowski et al. (2017)	♦					HM	conducting public health intervention		♦		
16	Šterk and Praprotnik (2017)				♦		GL	organizing rescue work		♦	♦	♦
17	Panigutti et al. (2017)	♦					HM	predicting epidemic transmission		♦		
18	Flahault et al. (2017)	♦					HM	conducting public health intervention, optimizing resource allocation	♦	♦	♦	
19	Steenbruggen et al. (2016)	♦					MPUP	processing real-time detection, developing pre-warning system			♦	
20	Gundogdu et al. (2016)	♦					MPUP	processing real-time detection			♦	
21	Ghurye et al. (2016)	♦					HM, SN	optimizing resource allocation	♦	♦	♦	
22	Zhang et al. (2016)			♦			ID	developing pre-warning system, making evacuation plan			♦	
23	Sekimoto et al. (2016)	♦			♦		HM	organizing rescue work			♦	
24	Cecaj and Mamei (2017)	♦					HM	processing real-time detection			♦	
25	Y. Chen et al. (2017)				♦		SN	predicting epidemic transmission		♦	♦	
26	Finger et al. (2016)	♦					HM	conducting public health intervention	♦	♦		
27		♦					HM	predicting epidemic transmission	♦	♦		

Table 4 (continued)

No.	Research publications	Types of mobile phone data					AP	Applications	EM phases			
		CDR	GPS	SMS	APP	Others			Mit	Pre	Res	Rec
	Tompkins and McCreesh (2016)											
28	Matamalas et al. (2016)	♦					HM	conducting public health intervention, optimizing resource allocation, delivering emergency announcement			♦	
29	Yasumiishi et al. (2015)					♦	HM	finding victims			♦	
30	Bengtsson et al. (2015)	♦					HM	predicting epidemic transmission		♦	♦	
31	Bharti et al. (2015)	♦					HM	presenting emergency impacts		♦	♦	
32	De Visser et al. (2015)				♦		ID	optimizing resource allocation		♦	♦	♦
33	Dobra et al. (2015)	♦					HM, SN	processing real-time detection			♦	
34	Reznik et al. (2015)			♦			MPUP	finding victims	♦	♦	♦	♦
35	Vogel et al. (2015)	♦					HM	predicting epidemic transmission	♦		♦	
36	Horsman and Conniss (2015)					♦	MPUP	stating policy/regulations	♦			
37	Farrahi et al. (2015)					♦	SN	predicting epidemic transmission	♦	♦		
38	Wesolowski et al. (2015a)	♦					HM	conducting public health intervention	♦	♦		
39	Wesolowski et al. (2015b)	♦					HM	predicting epidemic transmission	♦	♦		
40	Lima et al. (2015)	♦					HM, SN	conducting public health intervention, delivering emergency announcement	♦	♦		
41	Arai et al. (2015)	♦					MPUP	conducting public health intervention			♦	
42	Gao et al. (2014)	♦					SN, M-PU-P	presenting emergency impacts			♦	
43	Wesolowski et al. (2014)	♦					HM	conducting public health intervention	♦	♦		
44	Tatem et al. (2014)	♦					HM	conducting public health intervention	♦			
45	Pastor-Escuredo et al. (2014)	♦					MPUP	presenting emergency impacts			♦	
46	Nan Zhang et al. (2014)			♦			ID	developing pre-warning system		♦		
47	Oxendine and Waters (2014)			♦			GL	making evacuation plan			♦	
48	Lwin et al. (2014)			♦			ID	conducting public health intervention	♦			
49	Tizzoni et al. (2014)	♦					HM	predicting epidemic transmission	♦	♦		
50	Muehlegger and Shoag (2014)	♦					MPUP	stating policy/regulations	♦			
51	Andrade et al. (2018)	♦					HM	making construction plans				♦
52	Takahiro Yabe et al. (2018)		♦				GL, HM	processing real-time detection			♦	
53	Marzuoli and Liu (2018)					♦	GL	making evacuation plans, optimizing resource allocation			♦	♦
54	Kubicek et al. (2019)					♦	HM	(population distribution)				

Table 4 (continued)

No.	Research publications	Types of mobile phone data					AP	Applications	EM phases			
		CDR	GPS	SMS	APP	Others			Mit	Pre	Res	Rec
55	Babu et al. (2019)				♦		CI	developing pre-warning system, presenting emergency impacts, developing emergency-related platforms		♦	♦	
56	Jacobs et al. (2019)		♦			♦	GL, CI	making construction plans, presenting emergency impacts				
57	Hassan et al. (2019)			♦			ID	developing pre-warning system, delivering emergency announcements	♦		♦	
58	Tao et al. (2019)				♦		CI	developing pre-warning system	♦	♦	♦	
59	Takahiro Yabe et al. (2019a)		♦				HM	making evacuation plans				♦
60	Yin et al. (2019)					♦	GL	making evacuation plans		♦		♦
61	Takahiro Yabe et al. (2019b)		♦				HM	making evacuation plans				♦
62	Kumoji and Khan Sohail (2019)			♦			CI	processing real-time detection, conducting public health intervention			♦	
63	Andris et al. (2019)	♦					SN, GL	finding victims			♦	♦
64	Dar et al. (2019)		♦		♦		GL	processing real-time detection, delivering emergency announcement			♦	
65	Enenkel et al. (2019)			♦			CI	processing real-time detection, presenting emergency impacts			♦	

'AP' stands for 'Analysis perspective' and 'EM phases' represents 'phases of emergency management'. Six analysis perspectives are respectively human mobility (HM), social networks (SN), mobile phone usage pattern (MPUP), information diffusion (ID), geographic location (GL) and collected information (CI). The definitions of AP and Applications are consistent with Tables 2 and 3 .

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